TOWARDS MODELING DRIVER PERFORMANCE WITHIN CRASH-RELEVANT SCENARIOS AS VIRTUAL REFERENCE FOR THE SAFETY OF AUTOMATED VEHICLES

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ABSTRACT

Technological advancements have shown the viability of Automated Driving (AD) and have created high expectations on its benefits – especially in terms of safety. An important step for the introduction of AD on public roads is providing an acceptable proof of AD's positive risk balance compared to today's traffic consisting of human-driven vehicles. Simulation of scenarios has become an essential tool for such analyses, since field operative tests have been shown infeasible as only means for such proof. Nonetheless, data is needed from which to derive human driver behavior as a reference within simulated scenarios. This paper presents an approach for modeling human driver behavior within defined scenarios to serve as a reference for AD.

As a fundamental step to establish a suitable reference, we outlined the architecture of a parameterizable model of driver performance within crash-relevant scenarios, in which the driver model switches from a continuous control to a reactive behavior. The structure is based on well-established concepts like abstraction levels for the driving tasks, cognitive processes, and steps within information processing.

A decision tree-like structure serves as guidance for the modularization of the driver reaction within different scenarios, which allows creating modules of decision-making processes as well as implementation of possible reactions within a scenario.

To show the feasibility of the architecture and modules, and to demonstrate the applicability of the model, we conducted a driving simulator study of a scenario with a vehicle crossing from the right. Within the scenario, we varied the configuration of the potential crash (ego striking and borderline case) as well as apply two values of the available time to react. The study follows a within-subject design with 24 participants. The observed reaction choice, time and intensity were measured and then used to parameterize the driver model.

Braking was the most frequently observed driver reaction, while potential crash configuration apparently influences the reaction choice. The observed driver behavior was in line with assumptions based on the state of art, which were used for the initial architecture and decision making of the developed driver model. Re-simulating the scenario with the parameterized model led to a similar frequency of crashes as in the simulator study.

The experiment provided evidence that the driver model is built on reasonable assumptions for structuring the decision-making process and modeling dependencies between situational variables and reaction parameters. Due to sample characteristics such as age, the gathered parameters cannot serve as a general reference. However, it is not expected that a more diverse sample will disprove the assumptions for the model architecture.

The theoretical considerations for modeling the decision-making process and its dependency on situational variables make apparent which complexity lies within modeling driver reactions.

The proposed model for driver performance within crash-relevant scenarios aims to serve as a reference to prove the positive risk balance of AD. It provides a clear path for the establishment of a general reference model. Yet, the paper shows that the establishment of a baseline for all relevant scenarios comes with a tremendous effort and complexity.

OBJECTIVE

Over the last years, Automated Driving (AD) has been one of the most prominent research topics within the automotive industry, which was driven by advancements in sensing technology and improved processing power. Many players – some of which are traditional automotive OEMs integrating AD technology in their products and some startups or technology companies from other fields – have been showcasing the latest stage of demonstrator vehicles to be operating well on public roads. Few companies (e.g., Mercedes [1]) have released SAE Level 3 technology (see [2]), which allows automated operation within operating conditions at whose limits the driver is required to retake control of the vehicle. Other companies have instantiated SAE Level 4 operation, where no driver is required in defined areas (e.g., [3]). Still, no roll out of higher automation has been achieved at a larger scale.

One challenge, which automated driving is facing, is verifying the safety of AD technology, such that it is actually societally acceptable to have automated vehicles on public roads. Part of this challenge lies within the question, what level of safety should be achieved to be societally acceptable. Some authorities, for instance in Germany [4], have formulated the need for AD to achieve a positive risk balance compared to human drivers. Companies like Waymo have formulated a reference for safety in the form of a “Non-Impaired, Eyes ON the conflict” driver [5].

It has been shown, that proving the positive risk balance by means of on-road testing is economically infeasible, as even with simplifying assumptions a number of billions of km needs to be driven [3], [4]. An alternative approach for proving the positive risk balance lies within a scenario-based approach, which has for instance been established by the German PEGASUS Project [7]. A scenario-based approach allows focusing on Verification and Validation (V&V) activities that are particularly relevant for safety and thus promised an overall reduction in the testing effort.

Multiple definitions of the term *scenario* in the scope of automated driving have been proposed. A general overview of definitions related to scenarios for the validation and verification of automated driving systems (ADS) has been established in ISO 34501 [8]. It defines a **scenario** as the *sequence of the scenes integrated with the ADS(s)/subject vehicle(s), and its/their interactions in the process of performing (a) certain Dynamic Driving Task(s).* The exact separation of abstraction layers of scenarios is less relevant for this paper. Within the following, we will use the term **driving scenario**, which was established in the scope of prospective effectiveness assessment in the L3Pilot project [9]: *A driving scenario is a short period of driving defined by its main driving task (e.g., car following, lane change) or triggered by an event (e.g., an obstacle in the lane).* This definition can to a large extent be seen synonymous to the more abstract definition of **scenario category** in ISO 34501: *set of scenarios that share one or more characteristics.* Scenario-based testing activities can consist of a combination of tests in open fields, controlled field tests and simulation-based testing.

The challenge that comes with a scenario-based approach for verifying safety of automated driving is the need for representing the human driver as reference within the scenarios tested. Crash data provide a data source of driver reactions within defined safety-relevant scenarios, yet it needs to be noted that each accident contains only one driver reaction, which may represent statistical outliers of driver behavior. Moreover, the collection of accident data represents a tremendous effort to cover all the scenarios relevant for the safety validation of automated driving. Studies in simulators or controlled fields allow collecting the behavior of drivers within multiple defined scenarios, but the efforts associated with such studies also appear not to be economically feasible for verifying the safety of automated driving in completeness. An alternative lies within collecting a limited set of data on driver behavior and to establish a model of a driver that can be applied within simulation. Such models are referred to as **driver performance models** and can be built on scientific findings on driver behavior within safety-relevant situations and parameterized with data coming from various data sources.

In the following, an approach for modeling scenario-dependent driver performance data based on findings of reaction patterns within crash-relevant situations will be presented. The model is aimed at providing a modular framework for possible driver reactions within a driving scenario. The modularization should create ease of use and motivate reuse of software modules modeling driver behavior. Moreover, the model should allow multiple reactions within a concrete driving scenario based on probability distributions. The choice of reaction, the reaction time and the reaction intensity should be modeled in a way to make them dependent on situational parameters of the driving scenario.

RELATED WORK

The creation of a driver performance model depends on a detailed understanding of how a driver perceives and processes information and executes the driving task. Though driver behavior is still subject to research and will continue to be for some time, there are certain findings which can be used as the basis for driver modeling. In the following, fundamental findings on driver behavior will be presented and then put in the context of driver modeling. After that, we will focus on driver behavior modelling within crash-relevant situations, highlight existing models of driver performance and present relevant applications.

Structuring the driving task

Donges provides a fundamental structure of the driving tasks, which is not only used as reference of driver behavior but also as reference for the architecture of advanced driver assistant systems (ADAS) or automated driving systems [10]. Donges divides the driving task into three levels: navigation as the highest level, which comprises the selection of the correct route in either known or unknown surroundings, guidance as second level which includes tasks such as choosing the correct lane or executing a turning maneuver, and stabilization as the lowest level, which encompasses lane keeping or the control of the distance to the lead vehicle.

Another important classification of driver behavior is the classification of goal-oriented actions by Rasmussen [11]. He defines three categories of behavior: Knowledge-based behavior holds actions on which a person must actively apply and transfer knowledge from his/her experience to a situation which he/she has not experienced sufficiently often before. Rule-based behavior is applied in situations that occur often and in which a person can directly select an action based on rules learned from experience. Skill-based behavior is used for activities where no conscious control process needs to be applied as the situations or activity are well known to a person.

Table 1 provides a mapping between the levels of the driving tasks by Donges and Rasmussen based on [11].

Table 1.
Relations between levels of driving task [10] and classification of goal-oriented behavior [12] as given in [11]

	Knowledge-based	Rule-based	Skill-based
Navigation	x		
Guidance	x	x	x
Stabilization			x

Driver Modeling

A first use case for driver modelling was the application within traffic flow simulation, where the focus is less on simulating safety-relevant scenarios as an interaction of a small number of vehicles, but rather simulating entire traffic networks to investigate network capacities and congestion phenomena. The primary focus for such models is on modelling the following behavior of drivers. Most prominent models in this field are the Intelligent Driver Model (IDM) [13] or the driver model by Wiedemann [14], which finds its application in different simulation tools. While the IDM models driver behavior by means of a differential equation whose parameters can be set to mimic different driver attitudes, the model by Wiedemann aims at representing driver physiological processes, which are based on principles of looming and unconsciously keeping a desired headway. Parameters within the model point directly to interpretable parameters, like desired speed, desired time gap or gap at standstill.

More sophisticated approaches aim at modeling the driver as a complex control flow of a vehicle. Many approaches consider the three levels of the driving task by Donges [10], which splits driving into the navigation, the guidance and the stabilization layer. Klimke presents a driver model – also referred to as agent model – which follows these basic assumptions in its internal structure [15]. The model is intended to realize different tasks of maneuvers like the adaptation to a new speed limit. For this, a comprehensive architecture is presented, which covers all levels of the driving tasks and primary driver inputs (steering, throttle, braking), secondary inputs (e.g., lighting) as well as communication, and vehicle and system setup. The model was implemented as C++ class and published on GitHub.

A model aimed at covering the entire driving task is presented by [16], which aims at recreating physiological aspects of driver information processing. The model uses a stochastic process for modeling the driver's gaze behavior and some internal information processing. These may cause the model to perceive relevant information too late or not at all such that it may create crash-relevant situations or even crashes. This way, the model can be applied for effectiveness evaluation of automated driving systems, by either creating a baseline of simulated traffic or creating surrounding traffic for a single or multiple automated vehicles.

Driver behavior in crash-relevant situations

Everyday driving can be modeled as controller behavior (e.g., vehicle following and lane keeping), as for everyday-driving primarily skill-based or rule-based processes are of relevance. In contrast to everyday driving, crash-relevant situations are situations which the driver does not experience regularly. The driver needs to quickly select an action and implement it to avoid the collision with another object or to run off the road. The driver models which focus on the driver reaction to avoid a collision in crash-relevant situations are often referred to as driver performance models. Erbsmehl states, that the primary parameters for modeling the driver response in the crash-relevant situation are the reaction time and the reaction intensity [25].

When reaction times are analyzed or modeled, it is important to consider how they are defined. A high-level classification of the relevant elements of the overall reaction time is provided by Green [17]. Green defines the mental processing time – which in itself consists of *sensation*, *perception*, and *response selection and programming* –, the *movement time*, and the *device response time* [17]. If for instance a driver's reaction to a stimulus is observed by means of the deceleration of a vehicle, all mentioned elements of the reaction time will be executed until a deceleration of the vehicle can be observed. When modeling this deceleration, the device response time is typically not part of the driver model, but of the vehicle model.

Multiple studies have investigated the relation between reaction time and time-to-collision (TTC). Many of those show a positive correlation between TTC and reaction time of a driver, e.g., [18], [19] and [20], while [21] state an increase in reaction time at very small TTC. Apart from reaction time, the reaction choice of the driver model is particularly of relevance for crash avoidance or mitigation, which is especially relevant at conflicts at intersections, where evasive steering is a relevant option for the driver. Multiple studies have investigated, whether drivers execute a same direction swerve (SDS) or an opposite direction swerve (ODS) in crossing conflicts, with an SDS as pictured in Figure 1. The SDS is in [18] referred to as a *swerve into danger*: the driver executes an avoidance maneuver away from the other vehicle but at the same time into the direction in which the other vehicle is moving. From a consideration of the kinematics of the situation, in some of these situations a collision would have been avoidable with higher odds by braking and steering in the other direction. Weber et al. analyze whether driver execute a typical standard reaction within a scenario with another vehicle crossing the driver's path by means of driving simulator studies and accident analysis and found that driver's typically perform an SDS, which is assumed to be caused by a reflex action [19]. In a further study, they found that the probability of a standard reaction increases with lower time-to-arrival (TTA) values, which can be seen equivalent to TTC. Moreover, with lower TTA, less drivers showed a reaction consisting only of braking [18].

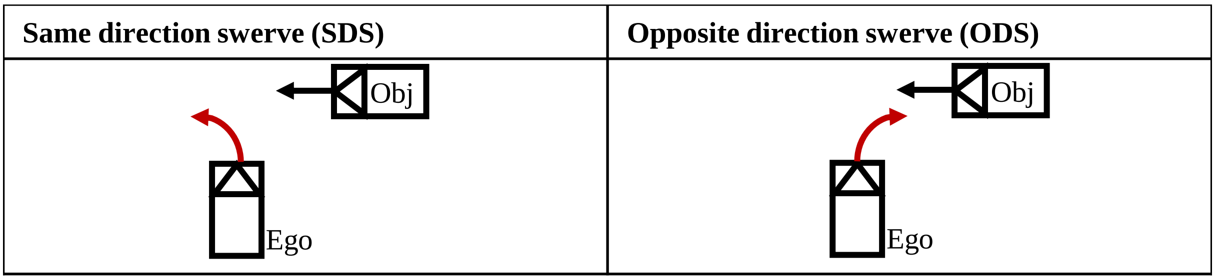


Figure 1. Definition of same direction swerve (SDS) and opposite direction swerve (ODS) based on [20]

Hu et al. also study driver behavior in crossing conflicts finding that an SDS-behavior is present in the scenario. How likely an SDS reaction is, depends, however, on the parameters of the scenarios [21] [22]. They show that the priority level (PL) is an important influence on the driver reaction. The PL expresses in a continuous number, how close one vehicle is to leaving the conflict zone before the other one enters it, as shown in Figure 2. The chance of an SDS, which Hu et al. consider as an irrational decision, increases with negative PL, while increased urgency of the reaction also increase the likelihood of an SDS.

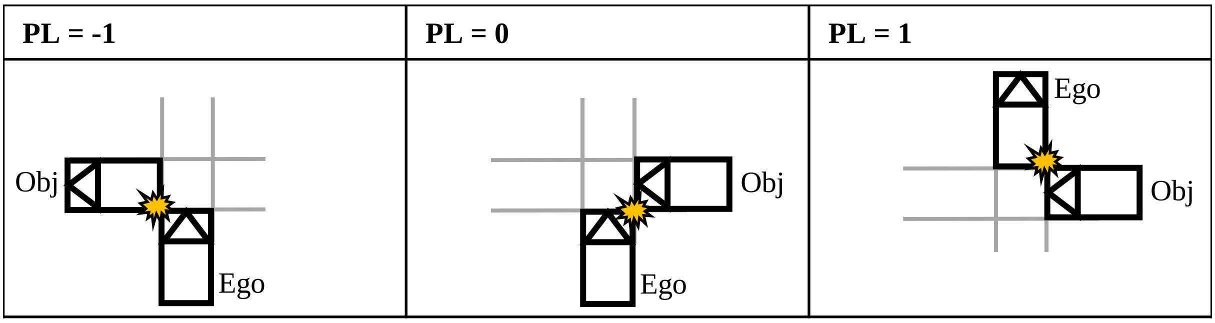


Figure 2. Characteristic values of the priority level (PL) as defined in [21]

Li et al. analyze different crash-relevant scenarios at intersections, where SDS behavior was also observed in a left turn across path (LTAP) scenario. Drivers executing a SDS had a significantly lower reaction time compared to drivers executing ODS [23].

Modelling evasive driving maneuvers

Based on physiological considerations, Lee showed that the control variable for braking is the derivative of the time-to-collision ($\dot{\tau}$), which drivers keep constant within a braking maneuver [26]. Yilmaz and Warren confirm the findings by Lee and further study the control process of braking, in which the driver shows a non-continuous behavior [27]. The brake pedal pressure is kept constant for a certain time until adjusted, based on $\dot{\tau}$. The $\dot{\tau}$-theory by Lee [26] in combination with the finding by Yilmaz and Warren [27] can be used to model driver behavior within braking situations, as applied by Roesener [28], where the braking application is modeled through a combination of an initial open-loop reaction continued by closed-loop control behavior.

Jurecki's and Stanczyk's [24] model for a straight crossing path scenario is one of the few models for modeling drivers' steering reactions in crash-relevant intersection scenarios. They model the steering wheel angle as a function of the lateral distance to the obstacle and the reaction time [18]. Their model is validated by comparing the modeled steering wheel trajectories with driving data from subject tests on a test track. They state that it is possible with their steering model to represent different driver behavior patterns using different parameterizations. However, a subdivision of the drivers into groups depending on their driving style is necessary [24]. A functional dependency of the parameters to modulate the reaction course does not seem to exist, which is why the use of predefined group-individual parameters is suggested [25].

A general statement regarding the steering behavior of drivers in crash-relevant maneuvers is given in [29]. According to the analyses, drivers tend to show an open-loop behavior, consisting of several, interrupted bell-shaped steering angle corrections [29]. The assumption of open-loop steering responses in lane changes on highways is presented in [28] and confirmed by a comparison with a closed-loop approach as a more accurate modeling approach.

Driver performance models and their application

Although driver behavior is still to a large extent subject to research, driver performance models have been used in different types of prospective safety assessments. The P.E.A.R.S. consortium [25] contributed to ISO technical report [26] which defines a method for prospective safety assessment. Within a prospective assessment, the baseline scenarios are needed, in which the system under assessment is expected to increase the safety. Baseline approach A as defined in [26] uses real world baseline scenarios, which may be reconstructed crashes or crash and near-crash situations from naturalistic driving data, also referred to as cases. In approach A these scenarios are used directly as baseline, such that the driver reaction is taken from the real case. Approach B modifies real world cases, which also makes it possible to derive more than one scenario from one real world case. Approach C generates synthetic scenarios, which are not directly linked to real world cases but uses data from real world cases or other driving data, such as driver behavior for generating synthetic cases.

While the modified scenarios are close enough to the real world for approach B, such that driver behavior in those cases is suitable as reference, approach C requires a driver model to produce baseline scenarios to serve as baseline within the prospective assessment. In [28], Fahrenkrog et al. presents a safety impact assessment study of an ADS for motorways which utilizes the model presented in [16]. The model uses a stochastic process for modeling the driver's gaze behavior, which in addition to some internal information processing, may cause the model to perceive relevant information too late or not at all such that it may create crash-relevant situations or even crashes. This way, the model can be applied for effectiveness evaluation of automated driving systems, by either creating a baseline of simulated traffic and creating surrounding traffic for a single or multiple automated vehicles. Within traffic scenarios spanning a stretch of motorway containing many vehicles, the model is used to represent the mechanisms leading to crash relevant situations as well as the driver reactions in crash-relevant situations. In cases where the ADS avoids a collision, it is still possible that a preceding vehicle collides with a heavily decelerating ADS.

Erbsmehl and Schebdat apply a simulation approach of driving scenarios with a driver performance model which uses distributions of reaction times and distributions of reaction intensity [29]. The model is applied in an assessment of a warning system.

Roesener et al. present a study where a traffic simulation with a driver model that explicitly models causation mechanisms for crash-relevant situations is combined with simulations of driving scenarios, where a driver performance model within crash-relevant driving scenarios is used as baseline [30]. The model implements results from a driving simulator study on the reaction time and reaction intensity to represent reference driver behavior within the simulated driving scenarios. In [9], the approach applied in [28] was applied for motorway scenarios and combined with a re-simulation of relevant real-world cases. For an urban ADS, the approach from [30] was refined and applied without the simulation of traffic scenarios.

In [31], Roesener builds upon the method established in [30] but uses a more sophisticated driver performance model to simulate the impact in rear-end and cut-in scenarios. The detailed model is presented in [32] and makes use of the findings from [33], but models the initial driver reaction as an open loop reaction. The model for evasive steering was built on the finding from [34] and uses low-level open-loop steering impulses to create the closed loop behavior.

Bärgman et al. perform a comparison of different driver performance models as references for the safety benefit of an integral safety systems [35]. One of the investigated models used a simple brake control sub-model with a constant jerk and the others use a linear relation between to the inverse of the optical time-to-collision, while for all the maximum deceleration is sampled from the same distribution. Apart from the first model, which uses no glance behavior model, all models use different models for the driver's glance behavior. The simulations show that the choice of model can have a significant effect on the safety benefits simulated.

Waymo present an alternative approach for modelling reaction times by implementing a belief update process in which the simulated driver initiates a reaction based on perceived violations to his prior belief [5]. This approach resolves two issues which driver performance models typically have in common. First, the update process takes into account an evolving traffic situation and thus allow to model the situation-dependence of the reaction time. Second, the modeling approach allows to define a stimulus in a scenario, even if no distinct event can be specified, which is only possible in controlled studies and often cannot be applied when using naturalistic data. The model is applied to rear-end crashes and near-crashes from the SHRP2 where the prior belief is modeled based on the looming principle (see [36]).

The UN ECE Regulation for the ALKS applies the modeled driver performance of a skilled human driver for deriving thresholds which situations are preventable or unpreventable [37]. The driving scenarios simulated are a cut-in, a cut-out with a slower vehicle in front of the vehicle cutting out, and the lead vehicle decelerating. The driver reaction is identified by means of a risk perception time, a delay in decision and a jerk time until the maximum deceleration. The regulation identifies clear definitions of the stimulus within the scenario. Simulation results show which configurations of the driving scenarios can still be considered avoidable.

METHOD

Modelling driver behavior is essential when carrying out a prospective effectiveness assessment of automated driving technology. When baseline cases are not taken from real world cases, where real driver behavior resulted in the crash or crash-relevant situation, driver behavior needs to be modeled within a synthetic scenario. While certain approaches like [16] use holistic models where safety-relevant situations are also caused by the driver model (e.g., by modeling a driver's inattentiveness), other approaches use predefined safety-relevant scenarios in which the opponent induces the crash-relevant situation and the vehicle under test must react to avoid a collision (e.g., as in [30]).

In the latter approach, driver behavior needs to be modeled specifically within the driving scenarios under investigation. It thus needs to be ensured, that the model used as reference within the baseline scenarios can produce a sufficiently realistic reaction to the safety-relevant situation. For this, the actual action of the driver needs to be implemented, which may consist of an open-loop action such as an initial brake application and a closed-loop control action, e.g., adjusting brake pressure during the course of the reaction. Apart from modelling the control action, their dependence on parameters within the driving scenario needs to be modeled (e.g., drivers may apply a stronger initial reaction in a situation with greater urgency). Moreover, multiple different driver reactions may be possible within a scenario. The reaction choice of the virtual driver may be modelled stochastically by choosing different controller implementations, while the probabilities of the different reaction choices may also depend on situational parameters. It should be noted that both of the approaches for using synthetic driving scenarios have their strengths and weaknesses. In general, modelling driving behavior remains a great challenge as the inner workings of a human being during driving are complex and affected by non-driving-related tasks.

The vastness of driving scenarios which need to be analyzed and possible options for driver reactions within a driving scenario result in a great overall complexity of aspects to be modeled. It is thus beneficial to instantiate one central driver model consisting of multiple interconnected modules which can be parameterized individually. Parameterizations should be easily defined and it should be possible to store and exchange them. This enables and motivates the reuse of models across multiple driving scenarios. In that way, it needs to be set for an assessment which modules should be used and how these should be parameterized.

In this work, we present a parameterizable driver model, whose architecture enables modularization and separate parameterization of model components, which in consequence eases reuse of model components creating a greater consistency across individual assessments and explainability of the model in the reporting of the setup, results and limitations of a prospective effectiveness evaluation. The remainder of this paper follows the following process steps:

0. Design architecture for a parameterizable driver performance model *
1. Identifications of the application of the model by
    a. Selecting a relevant driving scenario
    b. Selecting influencing scenario parameters
    c. Selecting suitable models for reaction
2. Plan and execute driving simulator study with a defined sample of drivers
3. Evaluate study
    a. Check if main design decisions for driver performance model are supported by study *
    b. Check if scenario parameters influence driver reaction within scenario
4. Use study as input for parameterization of model
    a. Decide for modeling of dependencies between scenario parameters and driver reaction
    b. Derive distributions for stochastic driver reaction
5. Re-simulate scenario of study with parameterized model
6. Validate results using study data (ideally with test data set)
7. *Apply model within prospective safety assessment*
   (The overall assessment needs to be validated as well)

These process steps serve as structure for this paper and explain how the model were to be applied in an effectiveness assessment. Steps marked with asterisk (*) are only relevant for this paper's scope and need not be executed in an application of the model: Step 0 presents the model architecture design, which is not a task to be repeated per application. Step 3.a validates this structure as part of the overall presentation of the model, supporting the overall design decision enabling reuse of the model. Step 7 encompasses the actual application of the model, which is out of scope of this paper. This application should follow the guidelines established by the P.E.A.R.S. consortium (see [26] and [27]), which also gives guidelines for a proper validation of the assessment. Apart from the steps listed above, this paper presents a discussion of the model, its setup und intended use.

DESIGN OF MODEL

The overall model architecture consists of two main design principles: A three-dimensional modularization of the driving task and a decision tree realizing the driver's reaction choice. The three dimensions along which the driving task is structured are:

1. The different layers of the driving tasks as defined by Donges [10]
2. The classification of target-oriented actions by Rasmussen [12]
3. The information processing chain divided into *perception*, *cognition* and *action*

These three dimensions of the driver reaction within crash relevant scenarios create a Rubik's Cube-like structure for the model. However, not all combinations of the categories create meaningful sub-processes. Such that not all of the elements of the Rubik's Cube are occupied by a software module which encapsulates physiological or statistical models recreating the driver behavior within a given driving scenario. The overall structure is presented in Figure 3. The navigation task typically only consists of knowledge-based processes, in areas where a driver needs to actively navigate, except for the sensory perception of environmental information, which is considered as a skill based-perception process. Within safety relevant scenarios, navigation is often not relevant. Only in special cases, additional workload by the navigation task may affect the driver's reaction but has not yet been subject to extensive research. Thus, navigation is only considered for completeness.

Skill-based processes typically do not require complex cognitive processes, such that they are modeled as sequences of perception and action. Skill-based reactions may be present as both, guidance, or stabilization tasks. Rule based actions are particularly relevant for the guidance layer as they encompass evasive maneuvers. For these, perception, cognition, and action are relevant processes, such that they are considered as modules within the driver model.

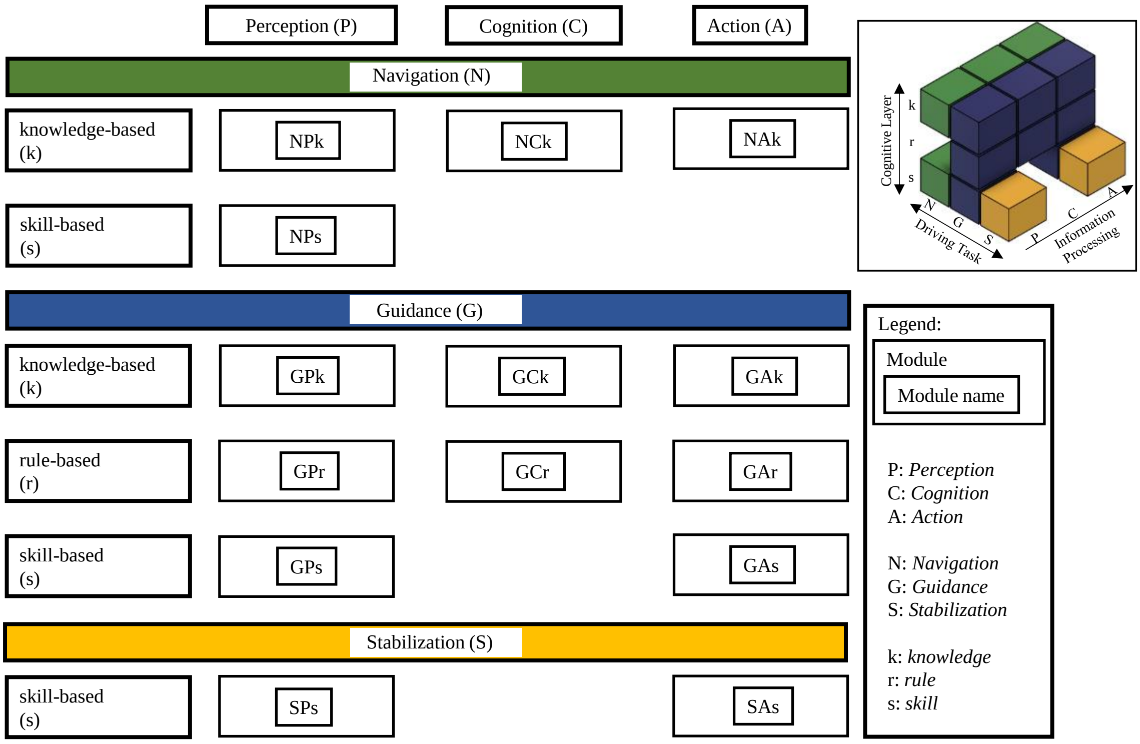


Figure 3. Generic architecture of the driver performance model

The model is implemented in Python and provides empty modules within its default configuration. The model uses OSI [38] as input data stream from the simulation environment. The model's output consists of the pedal positions and the steering wheel angle. At the time of writing, no harmonized driver model output interface existed, such that the output interface was implemented to suit the proprietary driver C-Struct of the simulation tool *Virtual Test Drive* by *Hexagon*, which was used as the tool for development and validation of the model. For an application these empty modules can be replaced by user-defined modules which can be set up as shown in Figure 4.

```
def GCk(Settings, Parameters, driver, ego):
    """Container for Guidance-Cognition-knowledge function calls"""
    import sys
    import os
    generic_duplicate_path \
        = os.path.join(Parameters.Parameter_generic_path, \
            "Guidance","G_Cognition")
            sys.path.append(generic_duplicate_path)
    ##################################
    # Import your functions below:
    #
    from cognition_stimulus_understanding \
        import cognition_stimulus_understanding
    [...]
    # Processing of perceived environment and checking for call for action
    driver = cognition_stimulus_understanding(Parameters,driver,ego)
    # Get reaction type:
    driver = cognition_decision_making_module(Parameters, driver)
    # Get reaction times:
    driver = cognition_decision_making_reaction_times(Parameters, driver)
    # Get reaction intensities:
    driver = cognition_reaction_intensity(Parameters, driver)
    [...]
    ##################################
    return driver
```

Figure 4. Python skeleton implementation module of driver reaction

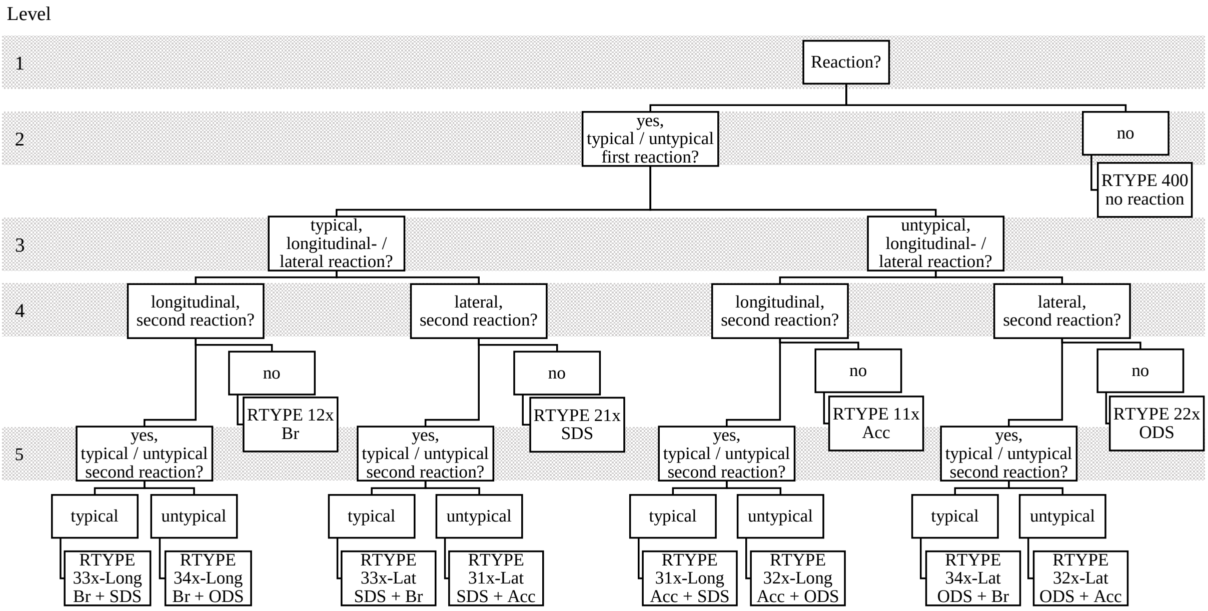
The structure presented above does not yet provide a structure for the possible driver reactions. Thus, additionally to the structure presented, different options for driver reactions need to be defined. For this, we structure possible driver reaction types – in the following called RTYPE – by means of a decision tree. The root node of the decision tree – the high-level RTYPE – considers whether a longitudinal (1xx) or lateral reaction (2xx) is executed or a combination of both (3xx). For the intervention a distinction is made, whether lateral or longitudinal acceleration is increased (11x resp. 21x) or decreased (12x resp. 22x), which is considered as mid-level RTYPE

Combined reactions are more complicated since according to [39], no truly parallel reactions exist. For this, we consider the different combinations of increase or decrease of lateral or longitudinal acceleration (31x – 34x) and add whether lateral or longitudinal intervention was first initiated (e.g., 31.x-Long for an increase in longitudinal acceleration, followed by an increase in lateral acceleration). A further distinction can be made on the level of the low-level RTYPE, which considers which and how driver control units (i.e., accelerator pedal, brake pedal, steering wheel) were used to influence the vehicle dynamics. The definitions of the high- and mid-level RTYPES are given in Table 2 and a decision tree leading to these is presented in Figure 5.

Table 2.
Definition of reaction types (RTYPE)

RTYPE	**Definition**
1xx	**Reaction influences longitudinal vehicle dynamics (longitudinal reaction)**
11x	Increase of longitudinal acceleration
12x	Decrease of longitudinal acceleration
2xx	**Reaction influences lateral vehicle dynamics (lateral reaction)**
21x	Increase of lateral acceleration
22x	Decrease of lateral acceleration
3xx	**Reaction influences longitudinal and lateral vehicle dynamics (combined reaction)**
31x-Long	Increase of longitudinal acceleration + Increase of lateral acceleration
31x-Lat	Increase of lateral acceleration + Increase of longitudinal acceleration
32x-Long	Increase of longitudinal acceleration + Decrease of lateral acceleration
32x-Lat	Decrease of lateral acceleration + Increase of longitudinal acceleration
33x-Long	Decrease of longitudinal acceleration + Increase of lateral acceleration
33x-Lat	Increase of lateral acceleration + Decrease of longitudinal acceleration
34x-Long	Decrease of longitudinal acceleration + Decrease of lateral acceleration
34x-Lat	Decrease of lateral acceleration + Decrease of longitudinal acceleration
4xx	**No reaction**
40x	Unchanged vehicle dynamics

The selection of the driver reaction in a single simulation run is based on a probabilistic decision tree, in which probabilities can be modeled in dependence of situational parameter (see example in Figure 7). The distinction into typical and not typical reactions refers to the finding by Weber [40].



Legend:
Br – Braking SDS – *Same-Direction-Swerving* (steering)
Acc – Accelerating ODS – *Opposite-Direction-Swerving* (steering)

Figure 5. Decision tree-like model of the stochastic decision-making process of the driver performance model

APPLICATION OF MODEL

Our aim is to derive a specific driver performance model for crash-relevant urban scenarios. Following the previously disclosed method, we first select a logical urban scenario and identify its characteristic description parameters, before implementing reaction algorithms.

Selection of scenario

Road accident statistics from Germany of the year of 2019 show that most of the crashes reported to the police happen in urban areas. Especially junctions including driveways are crash prone with more than 50 % of these crashes happening there [41]. Research from the Intersection 2020 project [42] identifies *straight crossing paths (SCP)*, *left turn across path – opposite direction*, and *left turn across path – lateral direction* as most relevant intersection car-to-car scenarios to focus on the enhancement of road safety at intersections. We chose to focus on straight crossing paths accidents with an opposing vehicle challenging from the right hand side of the ego vehicle (see Figure 6).

Relevant scenario parameters

From literature and related studies on driver behavior in crash-relevant scenarios, the time-to-collision and the projected crash constellation hypothetically influence the driver's reaction. Therefore we chose the initial time-to-conflict-point (TTCP) and the initial priority level (PL) as the two variables for our model. The start of the crash-relevant scenario is defined by the object vehicle becoming visible after being obstructed by a vehicle (Figure 11). Both values are measured at the time when the object vehicle becomes visible from the view point of the ego vehicle. The TTCP is calculated by the distance to conflict point (DTCP) and the current velocity of the ego vehicle. The PL is calculated by the following equations:

For $TTCP_{Obj} - TTCP_{Ego} < 0$: $$PL = \frac{TTCP_{Obj} - TTCP_{Ego}}{TTCP_{Obj,exit} - TTCP_{Obj}}$$ Equation (1)

For $TTCP_{Obj} - TTCP_{Ego} > 0$: $$PL = \frac{TTCP_{Obj} - TTCP_{Ego}}{TTCP_{Ego,exit} - TTCP_{Ego}}$$ Equation (2)

For $TTCP_{Obj} - TTCP_{Ego} = 0$: $$PL = 0$$ Equation (3)

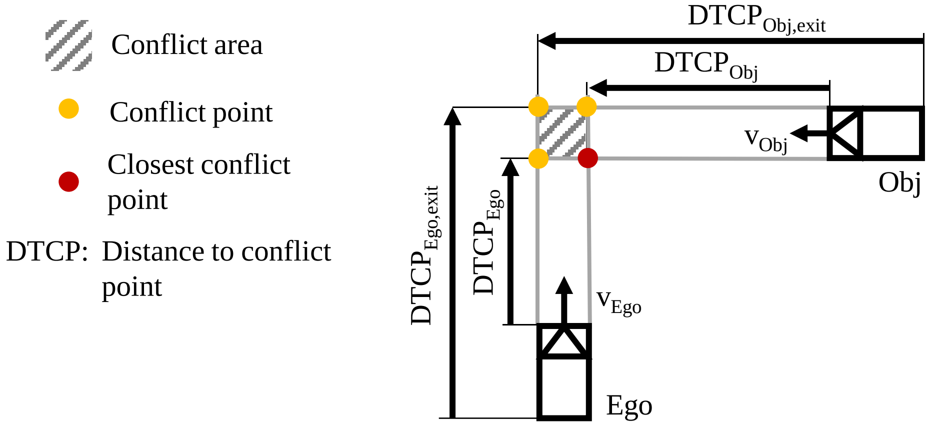


Figure 6. Description of the conflict

Implementation of model reactions

The process of human perception is modelled in a very simplified and ideal way in our driver performance model. Calculations required on the software side in relation to the perception of the environment are also assigned to the modules of perception. The perception process (incl. recognition) of the driver performance model consists of the detection of objects, the verification of the visibility of the objects, the computation of the scenario description variables TTCP and PL and the verification whether the visible object generates a request for action. To determine a reference time for the driver reaction, it is necessary on the software side to detect the time of occurrence of a perceptible crash-relevant situation. For this purpose, in the case of a suddenly appearing object, the earliest possible time is determined from which a point of the object would be visible to a driver without occlusion. The perception functions are distributed over the modules SPs, GPs, GPk and GCk (see Figure 3).

The reaction choice is modelled by the decision tree presented in Figure 5. The likelihood of a reaction choice depends on the scenario parameters TTCP and PL (see Table 7). The decision tree is located in module GCk.

For the reaction times, a dependency on the urgency of the scenario and the reaction type is considered. The reaction times are modeled by a truncated normal distribution around the mean of the measured reaction times of a driver population. For reaction times, 0 s or, for second reactions, the reaction time of the first reaction is set as the lower limit and the normal distribution is truncated accordingly. Reaction times are control unit specific and stochastically determined when simulating the driver performance model.

Driver responses to the steering wheel and pedals are modeled by reaction models from the literature, which are then fitted and parameterized to the data from our driving simulator study. For reaction intensity, we formed five discrete groups of reaction intensities for accelerator pedal actuation, braking, and steering: very low, low, medium, high, very high. For each reaction intensity, we parameterized the respective models with corresponding data from the study that are in the respective reaction intensity group. A reaction intensity is then stochastically determined specifically for the actuator when simulating the driver performance model and depends on the reaction time. The determination of a reaction intensity and reaction time is located in module GCk.

Regarding the modelling of the brake pedal stroke in crash-relevant situations, the results from [32] show that the assumption of an open-loop action of the driver provides good results. Based on this, we also model the longitudinal responses (step on the accelerator pedal or braking) by an open-loop response. The step on a (brake) pedal is modeled by the first-order transfer response of a system. During the simulation, the pedal position y at time n+1 is calculated discretely in time, considering the size of the time step dt, the parameters T and K, and the command variable u according to Equation (4).

$$y_{n+1} = \left(1 - \frac{dt}{T}\right) \cdot y_n + K \cdot \left(\frac{dt}{T}\right) \cdot u_n \qquad \text{Equation (4)}$$

For modelling the steering reaction of the drivers, we use an adapted formula based on the steering model of Jurecki [24]. Due to unsatisfactory results when fitting the model to the measurement data of the driving simulator study explained later, we extended the calculation formula by one term. This term is equivalent to an open-loop steering response, which is only time-dependent and not dependent on the lateral distance to the object. This extension goes along with the results from [43], according to which steering reactions are open-loop reactions. The adapted calculation formula can be found in Equation (5), where the parameter K_6 and the command variable u are introduced, which can be used to directly parameterize the maximum steering wheel angle (the reaction strength) during the steering reaction. The first two terms of Equation (5) resemble the discrete-time transfer behavior of a first-order system. The third term establishes a dependency of the steering wheel angle δ_{sw} on the lateral distance to the object and – by limiting $y_{lat,rel}$ – influences only the steering angle retraction.

$$\delta_{sw,n+1} = \left(\left(1 - \frac{dt}{W_4}\right) \cdot \delta_{sw,n} \cdot \frac{\pi}{180} + K_6 \cdot \left(\frac{dt}{W_4}\right) \cdot u_n + W_5 \cdot \left(\frac{dt}{W4}\right) \cdot y_{lat,rel,n}\right) \cdot \frac{180}{\pi} \qquad \text{Equation (5)}$$

$$\text{with } y_{lat,rel} = (y_{pos,obj} - y_{pos,ego}) + y_{offset} \qquad \text{Equation (6)}$$

$$y_{lat,rel} = \max(0, y_{lat,rel}) \qquad \text{Equation (7)}$$

$$y_{lat,rel} = min(0, y_{lat,rel}) \qquad \text{Equation (8)}$$

The steering and pedal reactions are implemented in the module SAs.

The parameterization of the driver reaction can be achieved using probabilistic trees in a JSON file as presented in Figure 7.

```
"node_on_reaction": {
    "required": ["branches", "weights"],
    "properties": {
        "branches": ["typical_reaction", "untypical_reaction"],
        "weights": {
            "independent_var": {
                "name": "ttcp",
                "val": [1.43,2.10]
            },
            "weights_branch_typical_reaction": [22,24],
            "weights_branch_untypical_reaction": [2,0]
        }
    },
    "node_on_typical_reaction": {
        "required": ["branches", "weights"],
        "properties": {
            "branches": ["long", "lat"],
            "weights": {
                "independent_var": {
                    "name": "ttcp",
                    "val": [1.43,2.10]
                },
                "weights_branch_long": [22,22],
                "weights_branch_lat": [0,2]
            }
        }
    },
    ...
}
```

Figure 7. JSON-Example for parameterization of driver reaction

SIMULATOR STUDY TO PROVE BASIC ASSUMPTIONS AND FOR PARAMETERIZATION

In the summer of 2020, we conducted a driver simulator study to proof the general assumptions on which the decision tree-like structure of the driver performance model is built up on and for the parametrization of the model. In general, the driver simulator study is utilized to answer the following research questions:

RQ1: How do drivers react in a crash-relevant intersection scenario where another vehicle crosses the first-person path from the right?

From literature research, we learned about reactions drivers show in crash-relevant scenarios. Therefore, we aim to answer the research question, whether the drivers show hypothetical typical first reactions. In our selected straight crossing path scenario at an intersection, these hypothetical typical first reactions are braking or a same direction swerving as steering reaction. In brief, the RQ2 and related hypothesis are:

RQ2: Do human drivers show typical first reactions?

Furthermore, we want to observe whether the scenario description parameters TTCP and PL influence the driver's reaction choice. For that, we formulate RQ3 and related hypothesis 2.1 and 2.2 as follows:

RQ3: Does the frequency distribution of the reaction types change when the TTCP or the PL are changed?

Hypothesis 3.1) There is a difference in frequency distributions of response types when the PL is changed.

Hypothesis 3.2) There is a difference in frequency distributions of response types when the TTCP is changed.

The driving simulator study was conducted in a static driving simulator with a 360° screen surrounding the ego vehicle at fka GmbH / the Institute of Automotive Engineering (ika). We invited 25 volunteers to join our study. One participant aborted the study after the test drive due to simulator sickness. Therefore, 24 valid data sets were obtained. Due to the Covid-19 pandemic, the participant pool was limited to employees of ika. Participants did thus not receive compensation for taking part in the study. The study took about 45 minutes to complete.

Of all 24 participants, three were female and 21 male, with a mean age of 27 years (SD=4.63; range: 20 to 37 years). On average, the participants obtained their driver's license 9.5 years ago and drove 8,290 km in the last year (SD=6975.46 km). Minimum mileage within the last year was 70 km/year and maximum mileage was 25,000 km/year.

Each participant filled in a data protection and participant information sheet and conducted a familiarization drive of about 6 minutes prior to the first measured drive to get used to the simulator. For the test drives, the participants were told to follow a lead vehicle with 50 km/h on a straight urban road, which crosses several intersections with green phased traffic lights. Each drive persisted for about 3 to 5 minutes until a crash-relevant scenario occurs. The participants were not briefed about the crash-relevant scenario they experienced in the drives. In each of the 5 separate urban drives, participants experienced one of the described scenarios (repeated-measures design, Figure 8). During the third drive, the participants experienced a scenario in which a challenging vehicle crossed from the left. This third drive was used to make the crash-relevant scenario more unpredictable to the participants. We randomized the order of the four relevant scenarios between the participants.

The four scenarios in which a vehicle crosses from the right differ in the values of the two independent variables TTCP and PL. The first TTCP value is chosen so that it is physically possible to avoid a collision by pure braking. For this purpose, a reaction time of 1.34 s is assumed for the first scenario, based on the time from the "Cologne model" [44] and a braking acceleration of -9 m/s² is assumed [44]. This results in a TTCP of 2.11 s. For the second TTCP condition, the reaction time is halved. In the neutral PL condition, both vehicles would arrive at the same time at the conflict area and collide with the front edges of the vehicles assuming that both vehicles travel with an unchanged trajectory. In the negative PL-condition, the ego vehicle would strike the most rearward side area of the object vehicle with 100 % overlap, which leads to a PL value of -0.71 considering the vehicle dimensions of both vehicles. Under ideal conditions, assuming that the ego vehicle is driven by the participant with exactly 50 km/h in the middle of the road, the object vehicle would travel 35.2 km/h. This is in the middle of the range of usual values in SCP crashes according to [42]. The exact starting position and velocity of the object vehicle is calculated online and adapted to the participant's vehicle velocity and position so that the independent variable values are realized. However, due to the method used to trigger the object vehicle (via the Simulation Control Protocol of Virtual Test Drive), the independent variable values were not exactly met during the study which led to a mean deviation of -0.011 s of the targeted TTCP condition and +0.05 of the targeted PL condition.

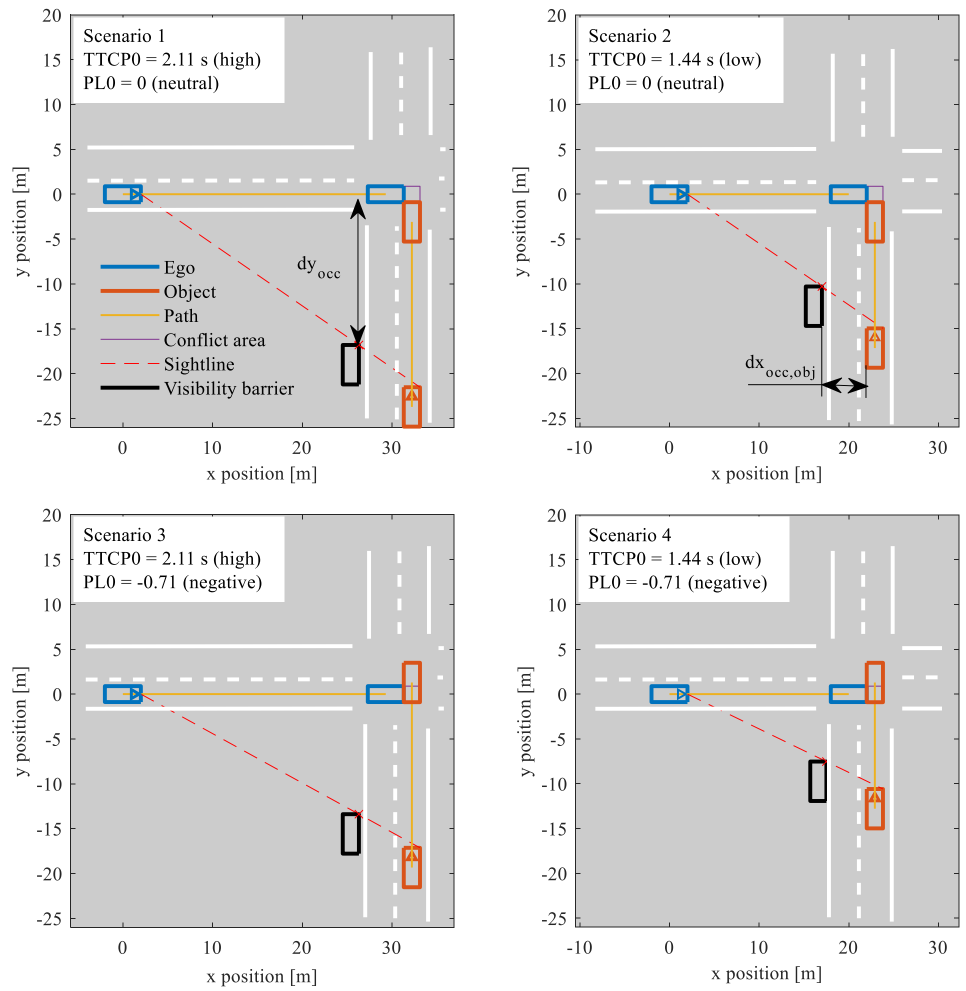


Figure 8. Scenarios used in the driver simulator study

Table 3.
Scenario parameters

	Independent variables		**Further scenario parameters**		
Scenario	TTCP0 [s]	PL0 [-]	theoretical v_{obj} [km/h]	dy_{occ} [m]	$dx_{occ,obj}$ [m]
1	2.11	0	35.2	-16.81	5
2	1.44	0	35.2	-10.29	5
3	2.11	-0.71	35.2	-13.39	5
4	1.44	-0.71	35.2	-7.53	4.5

The inputs on the steering wheel and pedals of each participant were traced and analyzed regarding reaction type, reaction time and intensity. Additionally, the participants answered a questionnaire after each drive to obtain subjective data, e.g., about the perceived criticality of the situation.

The following should be noted regarding the RTYPE classification of the study data:

- Actuator reactions that obviously occur after the crash-relevant situations have been thwarted or occur after the collision are not considered.
- In two cases, the accelerator pedal is depressed before the accelerator pedal is released and the brake pedal is depressed. This reaction pattern is not provided for in the RTYPE classification. It is classified here as RTYPE 11x, since in both situations the PL is increased and thus the initial accelerator pedal

depression has the greater effect than the brake pedal depression. This classification leads to a poor reproducibility of this same driver response.

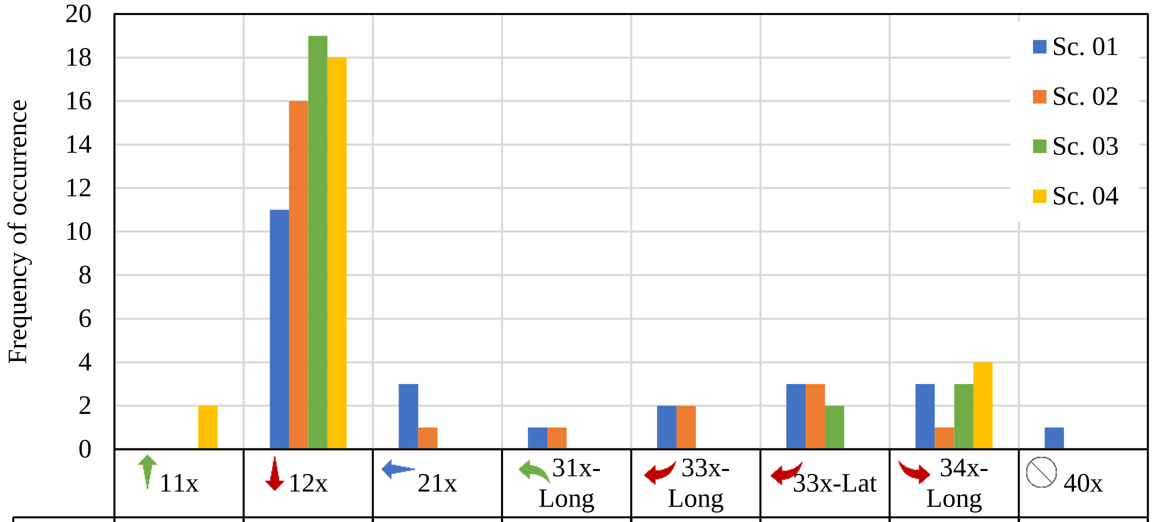
- In five cases, it appears that the driver is applying the brake pedal with the left foot as the accelerator pedal and brake pedal overlap for a short time. This very brief overlap is treated as if the accelerator pedal is released before the brake pedal is released.
- In one case, the driver first steers slightly in one direction and shortly afterwards steers more strongly in the other direction. Here, the steering response of the higher strength is used as the basis for the classification.
- In one case, the onset of braking and the onset of steering occur "simultaneously." In this case, the longitudinal reaction is assumed to be the initial reaction since the accelerator pedal was previously released.
- In two cases, the accelerator pedal is depressed during braking. Due to the very similar accelerator pedal and brake pedal travel, the accelerator pedal was probably inadvertently depressed with the same foot. The accelerator pedal is ignored for the classification.

RESULTS

The driving simulator study executed was used to confirm some of the assumptions the architecture of the driver performance model is based on. As following steps, the results were used to parameterize the model for the scenarios also investigated within the study. The parameterized model was then validated by comparing the frequency of crashes and impact speed with the outcomes of the study executed.

Driving Simulator Study

Figure 9 shows the frequency of occurrence of reaction types divided by scenario type. Among the scenarios, the frequency of occurrence of reaction types and the variability of reactions by the participants varies. The participants most frequently showed a single braking reaction (12x) along all scenarios. Steering to the right (ODS) only occurred after braking and never occurred as single reaction. Steering to the left (SDS) occurred after and before braking, after accelerating as well as a single reaction. Accelerating as single reaction occurred two times in Scenario 4. In Scenarios 1 and 2 (neutral PL), a higher variability in reaction types can be observed than in Scenarios 3 and 4 (negative PL). In Scenarios 1 and 2 (neutral PL), the participants steered sixteen times to the left (SDS) and four times to the right (ODS). In Scenarios 3 and 4 (negative PL), the participants steered two times to the left (SDS) and seven times to the right (ODS). Scenario 4 is the only scenario in which the initial reaction is always a longitudinal reaction.



	11x	12x	21x	31x-Long	33x-Long	33x-Lat	34x-Long	40x
Sc. 01	0	11	3	1	2	3	3	1
Sc. 02	0	16	1	1	2	3	1	0
Sc. 03	0	19	0	0	0	2	3	0
Sc. 04	2	18	0	0	0	0	4	0

Reaction types

Figure 9. Frequency of occurrence of reaction types in each scenario of the study, colored arrows indicating the effect of the reactions on the vehicle dynamics (green: increased acceleration, red: decreased acceleration (typically braking), blue: unchanged longitudinal acceleration)

Regarding our RQ2 about typical first reactions (braking or SDS steering (to the left)) of drivers, we analyzed the observed reaction types. From all of the 95 drives in which a reaction was shown, the participants showed a hypothetical first reaction in 90 of the rides. A Pearson Chi²-Test regarding the incidence of hypothetical typical (braking: [12x, 33x-Long, 34x-Long], SDS steering [21x, 33x-Lat]) vs. untypical first reactions in each scenario supports the hypothesis that the drivers show a hypothetical first reaction in all four scenarios ($X^2(1)$=19,174, p<.001 (Sc.1: *n*=23); $X^2(1)$=20,167, p<.001 (Sc.2: *n*=24); $X^2(1)$=16,667, p<.001 (Sc.4: *n*=24); (Sc.3: *n*=24) follows consequently, given that only typical first reactions were observed).

With the help of the frequency distributions of the reaction types per scenario, research question 3 is examined. The differences between the two PL conditions lie in the variety of reaction types and in the frequency of occurrence of individual reaction types. For example, pure braking reactions are observed 10 times (27 to 37) less frequently in total in the neutral PL condition than in the negative PL condition. In addition, seven different reaction types occur in total in the neutral PL condition, while four different reaction types can be observed in the negative PL condition. Thus, the results are consistent with hypothesis 3.1. Between the TTCP conditions at the same PL, there is a clear difference only for the frequency of pure braking reactions between scenario 1 and 2 (11 to 16). Based on the data, only a small influence of the TTCP on the driver's choice of action can be assumed. By the fact that almost every driver in the post-survey stated to have perceived the different temporal criticality between the scenarios, this small difference may nevertheless actually be due to the changed criticality. It should be noted that in the studies of [18] and [20], a discontinuity in the frequency course of braking and steering responses over a changed TTCP was observed. In Weber's study, braking reactions increased again at highly crash-relevant events, after the frequency of these had previously decreased with decreasing TTCP [18]. It is possible that the TTCP values in the present study were chosen in an unfortunate way to investigate the hypothesis, so that this discontinuity is reflected in the present study. For hypothesis 3.2, further research is needed at this point.

Parametrization of Driver Performance Model

The study's results are used to parametrize the previously described generic driver performance model. The frequency distribution of shown reaction types is used to parametrize the decision tree (see Figure 5) while the reaction times and reaction intensity are obtained from the traces of the pedal and steering wheel inputs.

In the study, driver behavior was recorded under two different PL and two different TTCP values and their combinations.

Since the literature review and our study show that drivers tend to change their behavior under different scenario conditions, this dependence of the probability of a reaction pattern is also reflected in the parameterization of the decision tree. We considered the influence of the scenario conditions, TTCP and PL, in different ways:

The influence of the priority level is discretized by creating two decision trees (see Figure 12) for different priority level ranges: one tree for the range of PL [-1, -0.4] and one tree for the range of [-0.4, 0.4]. During simulation, the appropriate decision tree is selected based on the priority level perceived by the perceptual module. It would also be possible to overlap ranges. A decision tree is then randomly selected in the overlapping area.

Up to five decisions are made within the decision tree. The probability of a decision is modeled using data from the driving simulator study. The probability is modeled per priority level at two support points of the TTCP. If the perception module of our driving performance model perceived a TTCP between the support points, the probability values at the point of perceived TTCP would be obtained by interpolation.

The assumption that driver behavior can be discretized into groups of similar PLs was not explored in our study. Rather, this assumption was made due to the lack of other experimental data. Also, the question of whether interpolation between TTCP support points is a valid procedure was not investigated in our driving simulator study neither, but would need to be investigated in follow-up studies. Our choice to incorporate the two scenario parameters differently in the parameterization of the decision tree served to demonstrate the possibilities of parameterization. However, we cannot claim that the assumptions made are correct.

In our model, the reaction time depends on the selected reaction type and on the TTCP perceived by the perception module of the driver performance model. This results in a small amount of data available in the study as a basis for the parameterization of reaction time, depending on the reaction type and TTCP condition. In order not to reduce the amount of data further, we refrain from distinguishing the PL condition, but without being able to claim that the PL has no influence on the reaction time.

From the study data, the average reaction time and the standard deviation are determined in order to model a normal distribution of the reaction time. The normal distribution is modelled as a truncated normal distribution so that implausible reaction times cannot arise. Implausible reaction times would exist if the reaction time takes on a negative value or if the reaction time of the second reaction is less than that of the first reaction. If a TTCP value between the two experimental conditions were perceived by the driver performance model, both the mean and the standard deviation would be interpolated. A reaction time is then determined probabilistically.

The conversion time between accelerator pedal release and brake pedal depression is parameterized as 0.2 s for all applicable reaction types. This means that the accelerator pedal is released 0.2 s before the parameterized brake reaction.

The reaction itself is modeled using the algorithms presented previously (Equation (4) – Equation (8)). To be able to model different reaction intensities, up to five reaction intensities per control element intervention are distinguished.

That is, a distinction is made between whether, for example, the brake pedal is depressed very lightly, lightly, moderately, strongly, or very strongly. A parameter set is determined for each of these reaction intensity groups.

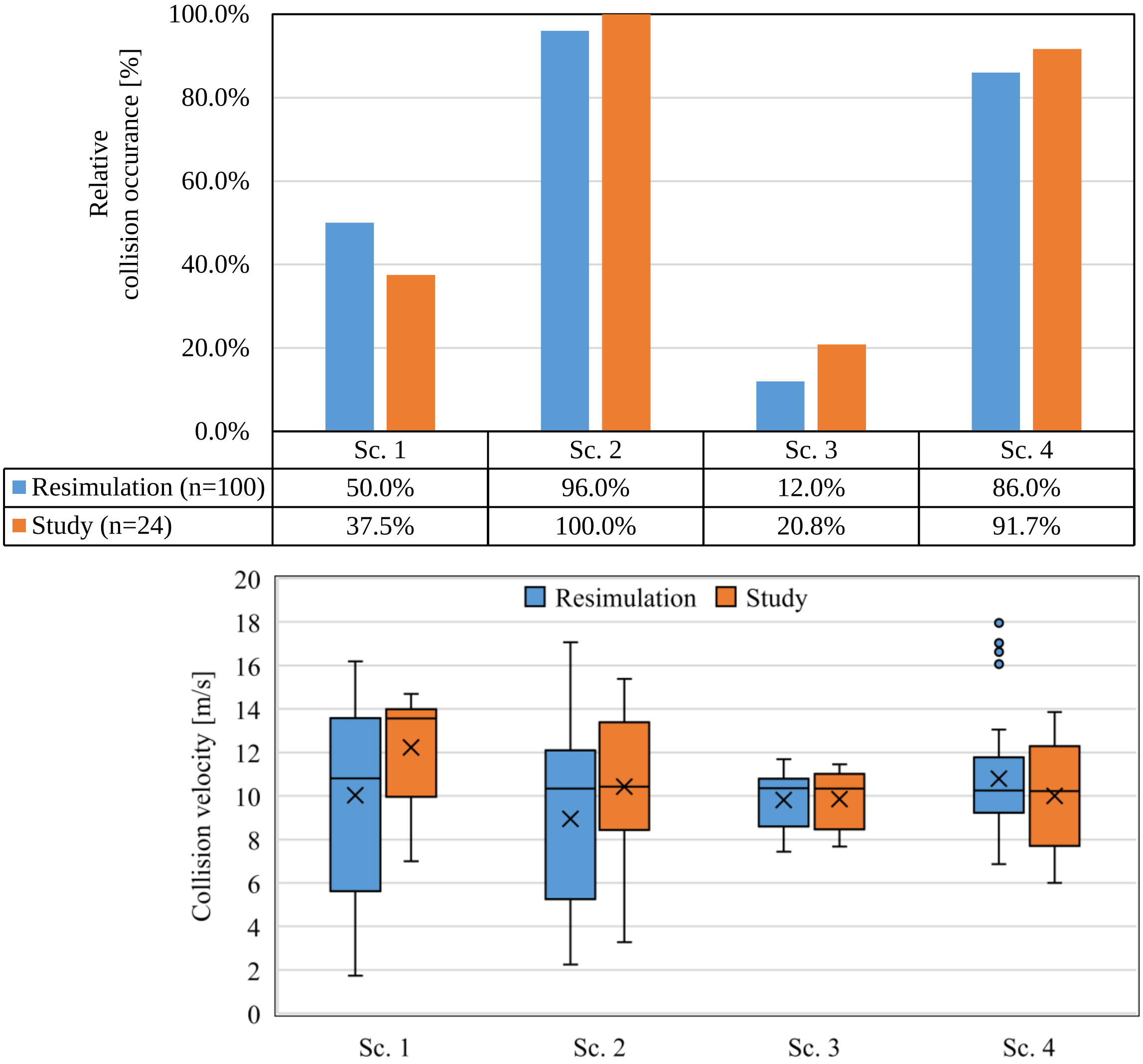
The parameterization of the reaction intensity is carried out in six steps:

1. aggregation of the study data with respect to identical controller responses (see Table 10)
2. definition of a characteristic value for the reaction intensity, e.g., maximum pedal position
3. definition of the limits of the reaction intensity groups (see Table 9)
4. set up a linear regression model of the reaction intensity over reaction time
5. determine the probability of occurrence of a reaction intensity group using the linear regression model
6. fitting the control algorithms with the measured data of a reaction intensity group (see Figure 13 and Figure 14).

In the driver performance model, a reaction intensity of the respective control unit is then determined probabilistically as a function of the reaction time. Depending on the reaction intensity group, the respective parameter set for the reaction algorithms.

Results from scenario re-simulation with the parameterized model

As a means of validation for how the model works in applications in effectiveness evaluation, the scenarios that have been simulated in the simulator study have been simulated also with the parameterized model to compare, whether the driver reaction produced by the model produces similar outcomes as observed in the study. For this, we compared the frequency of collisions in the simulated scenario from 100 repetitions with the stochastic model with that from the simulator study. Figure 10 shows that the frequency of collisions is comparable between the study and the simulated driver response.



	Sc. 1	Sc. 2	Sc. 3	Sc. 4
Resimulation (n=100)	50.0%	96.0%	12.0%	86.0%
Study (n=24)	37.5%	100.0%	20.8%	91.7%

Figure 10. Comparison of the collision occurrence and velocity between the re-simulation and study

For scenarios, in which collisions occurred, we compared the speed at impact of the ego vehicle. For scenarios 3 and 4 (negative priority level) resulting collision speed show comparable distributions. For scenarios 1 and 2 (neutral priority level) distributions of impacts speeds show some deviations, while it needs to be noted, that these scenarios show an overall larger spread in the outcomes of the driver reaction.

DISCUSSION

The model presented in this paper provides a framework for integrating driver behavior within a toolchain for effectiveness assessment of automated driving systems. It supplies a container for processes defining the action decision, the reaction time, and the magnitude of the reaction.

As in principle, the model will follow the complexity of the collection of scenario categories which was used in the effectiveness assessment. Scenario-based evaluations as such run the risk of the curse of dimensionality. While evaluation of systems operating on motorways may allow the evaluation of a rather simple framework of driving scenarios, comprehensive assessments of urban operating domains can result in a wide variety to be tested. It depends on the assessment approach and overall sample size of scenarios whether each scenario to be simulated needs to be simulated multiple times to cover different possible driver reactions.

A general advantage within scenario-based testing is the possibility to focus on certain scenarios, i.e., the most relevant ones, either in terms of overall risk, frequency of occurrence or possible consequences. The driver model framework presented is intended to focus on the hypothetical typical reaction, thus it may be justified to parameterize and simulate not all physically possible driver reactions.

An issue lies within the generalizability of driver reactions: In the study presented, 2x2 scenario configurations were analyzed between participants. The results showed that there was a difference in driver reaction between the simulated scenarios. In principle, the parameters obtained for these scenarios could be extrapolated linearly to cover more possible parameter configurations, but especially in terms of driver reaction, linear extrapolation does not appear plausible. To parameterize a model, that can cover all parameter combinations of the scenario to be studied, a large-scale study would need to be executed and statistical methods to be applied to parameterize the model for the entire value range of the scenario. To apply the model within other scenarios, an analysis is needed to see which scenario parameters have most influence on the driver reaction, either based on literature or on dedicated studies of the scenario.

Even though there is the danger of the curse of dimensionality, applying a modular model as presented, would enable sharing the findings of individual studies to gradually cover the most relevant scenarios, such that over time, driver modeling of such scenarios consists of less and less black spots and holistic assessment of e.g., level 4 automated driving systems will be feasible.

Similar to driver performance models in general, the proposed model faces the challenge, that for the situations simulated a stimulus for the reaction needs to be defined (for further elaboration see [5]). This is possible in experimental conditions, like in the study performed, where the object vehicle was occluded while the ego vehicle entered the intersection. The object vehicle becoming visible could easily be used as the stimulus for determining the reaction time. In other situations, this may not be possible. For instance in a rear-end scenario with the leading vehicle already in deceleration and then applying a sudden stronger deceleration, the brake lights could not be used as stimulus for the driver response. The model proposed in [5] could provide solution to this challenge and could be integrated as rule-based perception model on the guidance layer (GPr). While [5] discusses, how the evolving situation can affect the driver's reaction choice – which was also one of the core assumptions of our model, though achieved through simpler metrics referencing a distinct stimulus – it does not yet provide a solution how the reaction choice may be implemented. As shown in literature (e.g., [22]) as well as is the study presented, parameters of the situation have an effect on the reaction choice of the driver. The choice of reaction can of course have great impacts on the outcome of the crash-relevant situation. As long as no model exists, which can implement both, a reaction time independent of the stimulus as well an influence of situational parameters on the action decision, it needs to be carefully considered, which aspect may be more relevant to the targeted evaluation.

CONCLUSIONS AND FUTURE WORK

This paper presents an architecture and an application of a generic driver performance model. The model used a fundamental structuring of the driver reaction by means of the levels of the driving task by Donges [10], the structuring of goal-oriented activities by Rasmussen [12], and the general information processing chain of a driver. Using a structure as presented and standardized interfaces as OSI [38] will allow an easy exchange of model components and an easier documentation of the baseline simulations within a predictive effectiveness assessment, which would ultimately result in a greater acceptance and comparability of results.

As next steps, the model needs to be parameterized for more driving scenarios, using greater samples to cover the entire driver population in terms of age, gender or driving experience. The parameterization of different scenarios can be driven by its intended applications, e.g., by focusing first on scenarios relevant for motorway ADS. The modularization of the model and the separation of modeling and parameterization would allow an easy reuse of components and parameter sets established. Moreover, more complex models for perception and cognition could be integrated depending on the use case. A tradeoff should be considered between a comprehensive modeling of the actual perception and cognition processes and a more straightforward though simplified approach using distributions of reaction times.

In principle, the application of the model faces the same pitfalls as scenario-based testing for ADS in general, but will also profit from its advancements. Research in scenario-based testing tries to identify the most relevant scenarios for an ADS such that an efficient yet comprehensive evaluation process can be established, for instance using a scenario framework as presented in [45]. This reduction of the scenario-space will also reduce the effort for parameterizing the driver performance model. Given that the variety of driver reactions requires the modeling of stochastic processes, each concrete scenario needs to be simulated multiple times, increasing simulation efforts. At the same time – once a concrete scenario has been simulated using the model – the results can be reused multiple times, in contrast to the V&V process of an ADF where each system iteration needs a repetition of simulations. Furthermore, findings on the typical driver reactions within crash-relevant scenarios (see [40]) may provide an acceptable reduction in driver reactions to be considered.

Within future work, we will establish a connection between the driver performance model presented and models that cover normal driving phase. A suitable model for this is the model by Klimke, as it follows a similar structuring of the driving task [15]. This may allow a comprehensive model that includes traceable crash causation mechanism which can also be used to induce crash-relevant situations. This way, the model could also be used within a traffic simulation-based assessment, where the causation of a crash does not need to be scripted within the scenario but is a result from the interaction of driver models. This approach would be similar to the approach in [16] but at the same time allows a more detailed modelling of driver reaction within the crash relevant scenario.

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APPENDIX

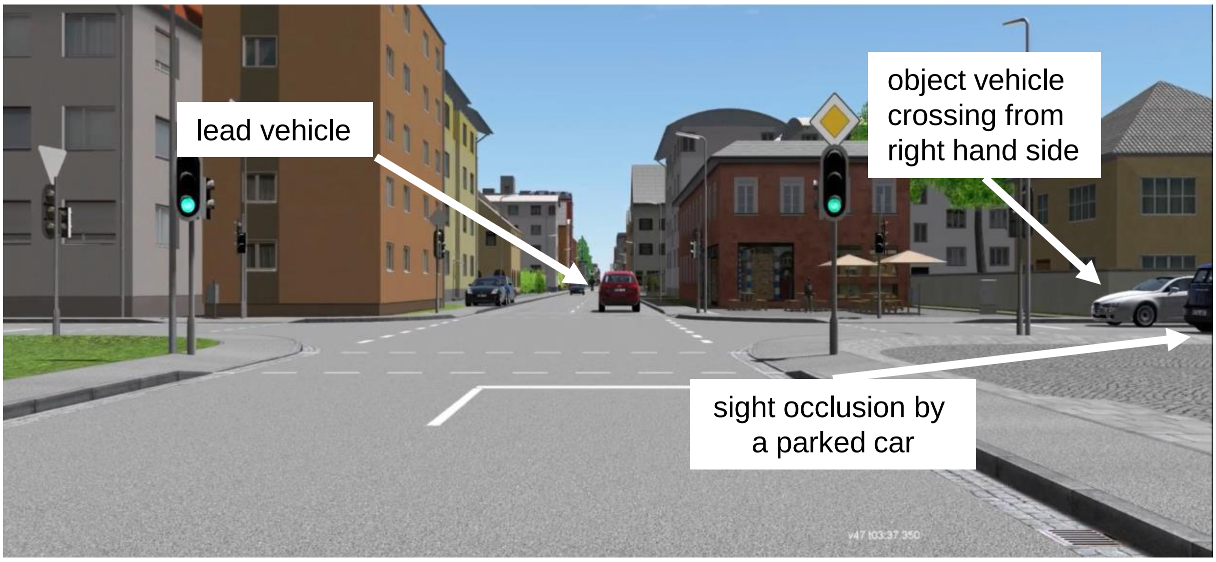

Figure 11. Annotated screen picture of scenario no. 3 of the study

Table 4.
Low-level RTYPE classification (1 of 3)

No.	Effect	Mid-level code	Control unit usage sequence	Control unit action	Low-level code
	RTYPE 1xx: longitudinal reaction				**1xx**
1	increase longitudinal acceleration	**11x**	A	Ai	11-1
2		**11x**	B	Bd	11-2
3		**11x**	A-B	Ai Bd	11-3
4		**11x**	B-A	Bd Ai	11-4
5	decrease longituinal acceleration	**12x**	B	Bi	12-1
6		**12x**	A-B	Ad Bi	12-2
7		**12x**	B-A	Bi Ad	12-3
8	undefined longitudinal acceleration	1xx	A-B	Ai Bi	1x-1
9		1xx	B-A	Bi Ai	1x-2
10		1xx	A-B	Ad Bd	1x-3
11		1xx	B-A	Bd Ad	1x-4
	RTYPE 2xx: lateral reaction				**2xx**
12	increase lateral acceleration	**21x**	S	Sl	21-1
13		**21x**	A-S	Ad Sl	21-2
14		**21x**	S-A	Sl Ad	21-3
15	decrease lateral acceleration	**22x**	S	Sr	22-1
16		**22x**	A-S	Ad Sr	22-2
17		**22x**	S-A	Sr Ad	22-3
	RTYPE 3xx: combined reaction (1 of 3)				**3xx**
18	increase longitudinal acceleration + increase lateral acceleration	**31x-Long**	A-S	Ai Sl	31-1-Long
19		**31x-Long**	B-S	Bd Sl	31-2-Long
20		**31x-Long**	A-B-S	Ai Bd Sl	31-3-Long
21		**31x-Long**	B-A-S	Bd Ai Sl	31-4-Long
22		**31x-Long**	A-S-B	Ai Sl Bd	31-5-Long
23		**31x-Long**	B-S-A	Bd Sl Ai	31-6-Long
24		**31x-Lat**	S-A	Sl Ai	31-1-Lat
25		**31x-Lat**	S-B	Sl Bd	31-2-Lat
26		**31x-Lat**	S-A-B	Sl Ai Bd	31-3-Lat
27		**31x-Lat**	S-B-A	Sl Bd Ai	31-4-Lat

Legend
A: Accelerator
B: Brake pedal
S: Steering
i: increase
d: decrease
l: left, r: right
Long: longitudinal
Lat: lateral

Table 5.
Low-level RTYPE classification (2 of 3)

No.	Effect	Mid-level code	Control unit usage sequence	Control unit action	Low-level code
	RTYPE 3xx: combined reaction (2 of 3)				**3xx**
28	increase longitudinal acceleration + decrease lateral acceleration	**32x-Long**	A-S	Ai Sr	32-1-Long
29		**32x-Long**	B-S	Bd Sr	32-2-Long
30		**32x-Long**	A-B-S	Ai Bd Sr	32-3-Long
31		**32x-Long**	B-A-S	Bd Ai Sr	32-4-Long
32		**32x-Long**	A-S-B	Ai Sr Bd	32-5-Long
33		**32x-Long**	B-S-A	Bd Sr Ai	32-6-Long
34		**32x-Lat**	S-A	Sr Ai	32-1-Lat
35		**32x-Lat**	S-B	Sr Bd	32-2-Lat
36		**32x-Lat**	S-A-B	Sr Ai Bd	32-3-Lat
37		**32x-Lat**	S-B-A	Sr Bd Ai	32-4-Lat
38	decrease longitudinal acceleration + increase lateral acceleration	**33x-Long**	B-S	Bi Sl	33-1-Long
39		**33x-Long**	A-B-S	Ad Bi Sl	33-2-Long
40		**33x-Long**	B-A-S	Bi Ad Sl	33-3-Long
41		**33x-Long**	B-S-A	Bi Sl Ad	33-4-Long
42		**33x-Lat**	S-B	Sl Bi	33-1-Lat
43		**33x-Lat**	A-S-B	Ad Sl Bi	33-2-Lat
44		**33x-Lat**	S-A-B	Sl Ad Bi	33-3-Lat
45		**33x-Lat**	S-B-A	Sl Bi Ad	33-4-Lat
46	decrease longitudinal acceleration + decrease lateral acceleration	**34x-Long**	B-S	Bi Sr	34-1-Long
47		**34x-Long**	A-B-S	Ad Bi Sr	34-2-Long
48		**34x-Long**	B-A-S	Bi Ad Sr	34-3-Long
49		**34x-Long**	B-S-A	Bi Sr Ad	34-4-Long
50		**34x-Lat**	S-B	Sr Bi	34-1-Lat
51		**34x-Lat**	A-S-B	Ad Sr Bi	34-2-Lat
52		**34x-Lat**	S-A-B	Sr Ad Bi	34-3-Lat
53		**34x-Lat**	S-B-A	Sr Bi Ad	34-4-Lat
54	undefined longitudinal acceleration + increase lateral acceleration	3xx	A-B-S	Ai Bi Sl	3x-1-Long
55		3xx	B-A-S	Bi Ai Sl	3x-2-Long
56		3xx	A-S-B	Ai Sl Bi	3x-3-Long
57		3xx	B-S-A	Bi Sl Ai	3x-4-Long
58		3xx	A-B-S	Ad Bd Sl	3x-5-Long
59		3xx	B-A-S	Bd Ad Sl	3x-6-Long
60		3xx	B-S-A	Bd Sl Ad	3x-7-Long
61		3xx	S-A-B	Sl Ai Bi	3x-1-Lat
62		3xx	S-B-A	Sl Bi Ai	3x-2-Lat
63		3xx	S-A-B	Sl Ad Bd	3x-3-Lat
64		3xx	S-B-A	Sl Bd Ad	3x-4-Lat
65		3xx	A-S-B	Ad Sl Bd	3x-5-Lat

Legend
A: Accelerator
B: Brake pedal
S: Steering
i: increase
d: decrease
l: left, r: right
Long: longitudinal
Lat: lateral

Table 6.
Low-level RTYPE classification (3 of 3)

No.	Effect	Mid-level code	Control unit usage sequence	Control unit action	Low-level code
	RTYPE 3xx: combined reaction (3 of 3)				**3xx**
66	undefined longitudinal acceleration + decrease lateral acceleration	3xx	A-B-S	Ai Bi Sr	3x-1-Long
67		3xx	B-A-S	Bi Ai Sr	3x-2-Long
68		3xx	A-S-B	Ai Sr Bi	3x-3-Long
69		3xx	B-S-A	Bi Sr Ai	3x-4-Long
70		3xx	A-B-S	Ad Bd Sr	3x-5-Long
71		3xx	B-A-S	Bd Ad Sr	3x-6-Long
72		3xx	B-S-A	Bd Sr Ad	3x-7-Long
73		3xx	S-A-B	Sr Ai Bi	3x-1-Lat
74		3xx	S-B-A	Sr Bi Ai	3x-2-Lat
75		3xx	S-A-B	Sr Ad Bd	3x-3-Lat
76		3xx	S-B-A	Sr Bd Ad	3x-4-Lat
77		3xx	A-S-B	Ad Sr Bd	3x-5-Lat
	RTYPE 4xx: no reaction				**4xx**
78	no reaction	**40x**	n.a.	n.a.	40-0
79		**40x**	A	Ad	40-1

Legend
A: Accelerator
B: Brake pedal
S: Steering
i: increase
d: decrease
l: left, r: right
Long: longitudinal
Lat: lateral

Table 7.
Parameters and dependencies of model variables RTYPE, RT and RINT

	Reaction type (RTYPE)	**Reaction time (RT)**	**Reaction intensity (RINT)**
Dependencies	Scenario dependent (TTCP, PL)	Scenario dependent (TTCP), reaction type dependent (RTYPE)	Reaction time dependent (RT)
Parameter	Probability of occurrence of a RTYPE	Control unit specific reaction time (mean value, standard deviation)	Control unit specific and algorithm specific parameters

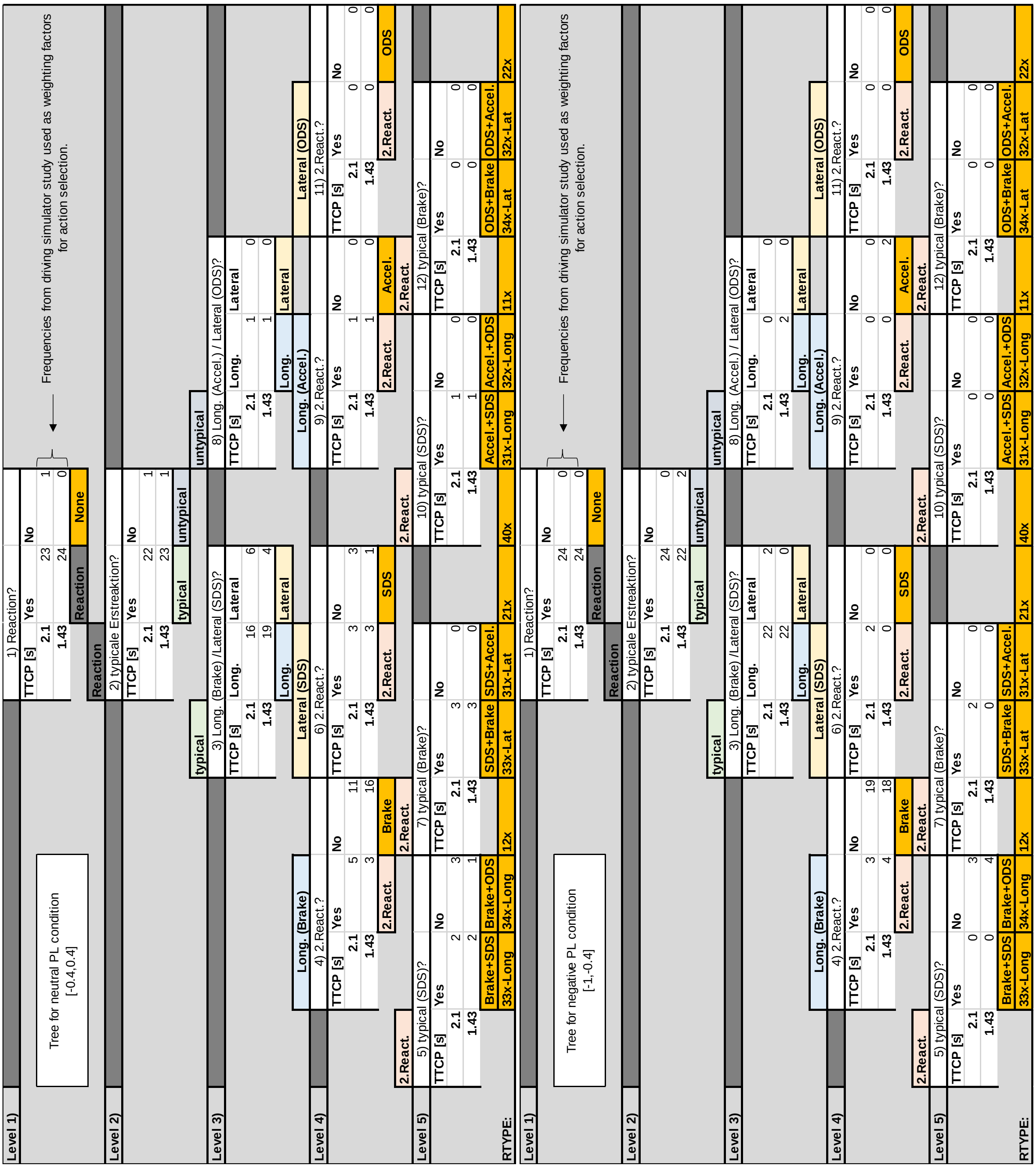

Figure 12. Parametrized decision trees for the priority level range of [-0.4,0.4] and [-1,-0.4]

Table 8.
Parameter values of the RTYPE-specific reaction times

ØTTCP [s]	**RTYPE**	**Frequency of occurrence in study**	**RT [s]**					
			Accelerator pedal		**Brake pedal**		**Steering wheel**	
			MW	**Std.**	**MW**	**Std.**	**MW**	**Std.**
1.42	**11x**	2	0.642	0.153	-	-	-	-
1.43	**12x**	34	-	-	0.826	0.223	-	-
1.45	**21x**	1	-	-	-	-	1.267	0.000
1.42	**31x-Long**	1	0.633	0.000	-	-	0.917	0.000
1.42	**33x-Long**	2	-	-	0.717	0.047	1.025	0.153
1.43	**33x-Lat**	3	-	-	0.917	0.202	0.850	0.188
1.43	**34x-Long**	5	-	-	0.757	0.158	1.123	0.119
2.10	**12x**	30	-	-	0.896	0.240	-	-
2.11	**21x**	3	-	-	-	-	1.628	0.208
2.10	**31x-Long**	1	1.433	0.000	-	-	1.833	0.000
2.09	**33x-Long**	2	-	-	0.950	0.236	1.967	0.613
2.11	**33x-Lat**	5	-	-	1.437	0.140	1.083	0.216
2.10	**34x-Long**	6	-	-	0.783	0.211	1.189	0.323

Table 9.
Key values for the subdivision of reactions into reaction intensity groups

Control unit reaction:	**Operate accelerator pedal**		**Operate brake pedal**		**Steer left**		**Steer right**	
Key value:	Max. accelerator position [0-1]		Max. brake pedal position [0-1]		Max. steering wheel angle [°]		Max. steering wheel angle [°]	
RINT group	From	To	From	To	From	To	From	To
1 (very low)	0	0.2	0	0.2	0	24	0	24
2 (low)	0.2	0.4	0.2	0.4	24	48	24	48
3 (medium)	0.4	0.6	0.4	0.6	48	72	48	72
4 (high)	0.6	0.8	0.6	0.8	72	96	72	96
5 (very high)	0.8	1	0.8	1	96	120	96	120

Table 10.
Aggregated control unit reactions and frequency of occurrence in study data

Control unit reaction	**Origin of the parameters for the reaction intensity specific algorithms**						
	Aggregated RTYPEs	**Frequency of the RINT group in study data**					
			RINT group				
		∑	**1**	**2**	**3**	**4**	**5**
Operate accelerator pedal	11x, 31x-Long, 32x-Long, 31x-Lat, 32x-Lat	4	0	0	0	0	4
Operate brake pedal	12x, 33x-Long, 33x-Long, 33x-Lat, 34x-Lat	87	1	1	5	10	70
Steer left	21x, 31x-Lat, 33x-Lat, 31x-Long, 33x-Long	18	4	7	1	1	5
Steer right	22x, 32x-Lat, 34x-Lat, 32x-Long, 34x-Long	11	2	5	2	2	0

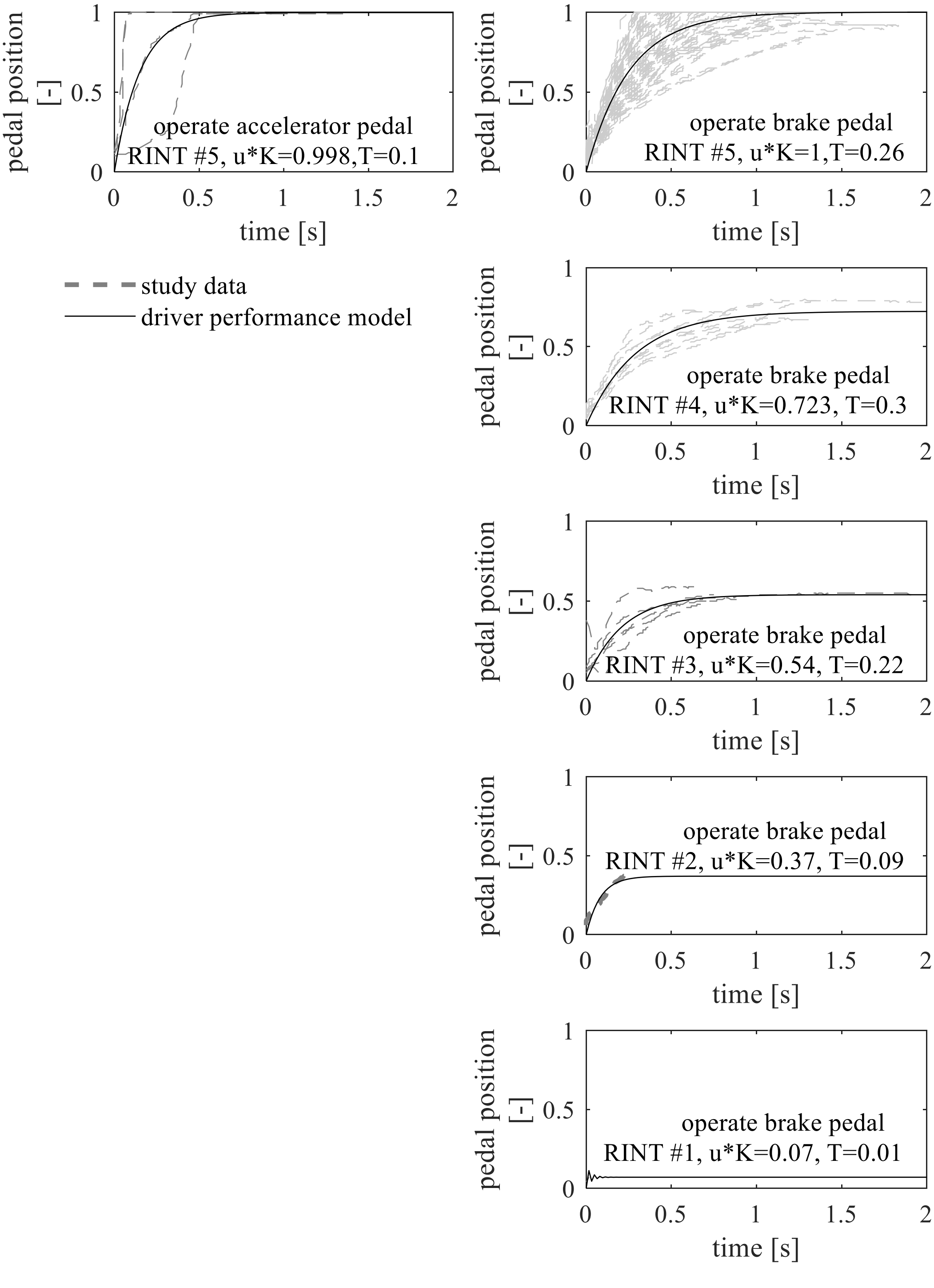

Figure 13. Reaction intensity specific parameters of the pedal control algorithm of the driver performance model

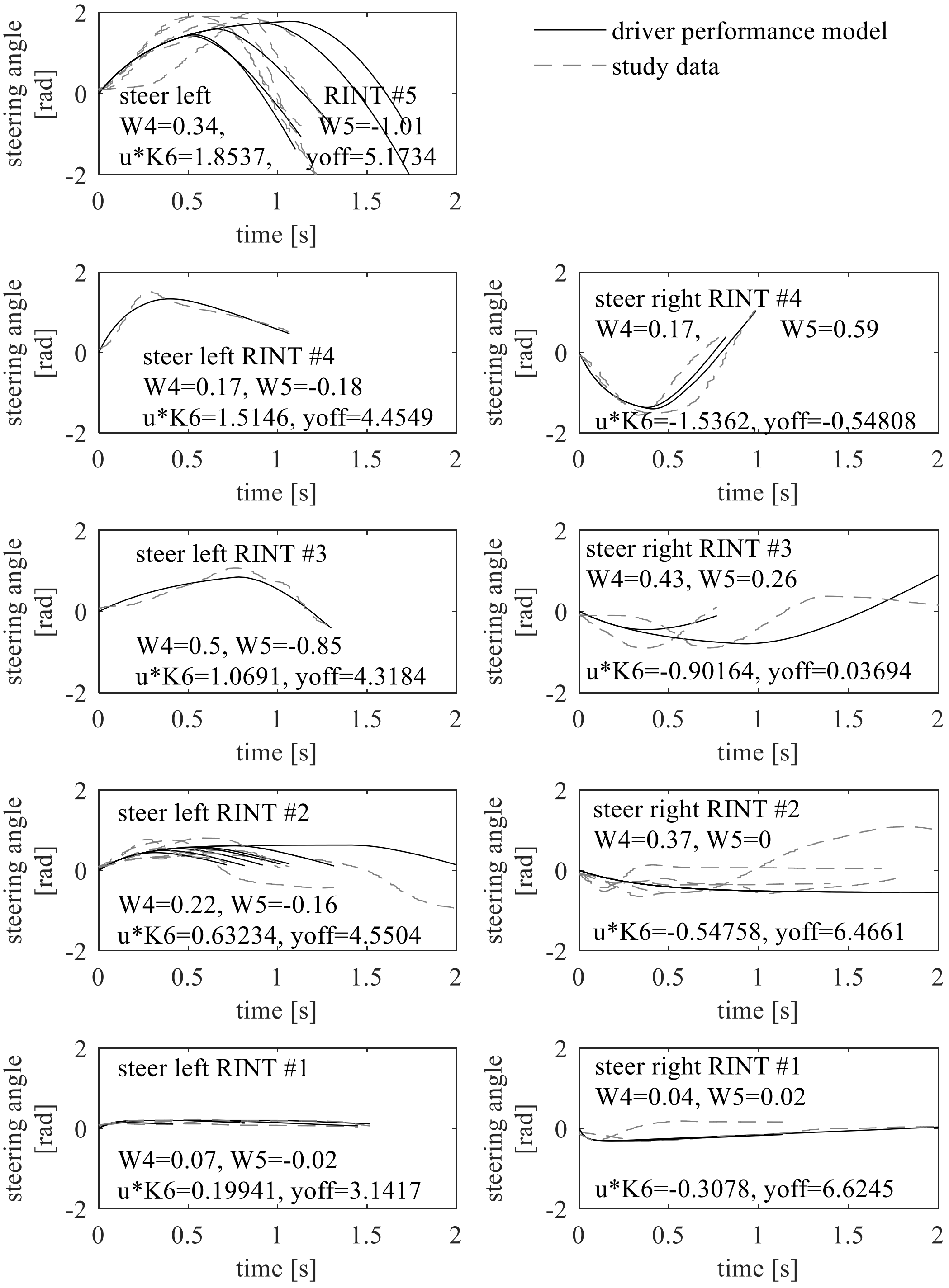

Figure 14. Reaction intensity specific parameters of the steering algorithm of the driver performance model

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  "required": ["scenario", "RTYP"],
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    },
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        "classification": "typical",
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            },
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            "std": [0.223,0.240],
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            "weights_mid": [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0.,...],
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            "weights_very_high": [1,1,1,1,1,1,0.9999,0.9999,0.9999,0.9998,0.9997,0.9996,0.9994,...]
          }
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            },
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              ...
            },
            ...
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        }
      },
    ...
    }
  }
}
```
Figure 15. Exemplary implementation of decision tree in model based on study results