Survey

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The role of driver models in testing highly-automated driving: a survey

Die Rolle von Fahrermodellen für das Testen hoch-automatisierter Fahrfunktionen: Eine Übersicht

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Abstract: A particular challenge in the development of highly-automated driving functions is the validation of these systems. A possible approach to cope with the validation effort is the use of simulations. Thereby, simulators can be used in various aspects of the validation process. For a meaningful application of simulators, individual aspects of reality are replaced by models. Based on an analysis of the different use cases, the various driver models from the state-of-art will be examined in this article with regard to their conceptual suitability for safeguarding highly automated driving functions.

Keywords: highly-automated driving; scenario-based testing; simulation; verification and validation.

Zusammenfassung: Eine besondere Herausforderung bei der Entwicklung hoch-automatisierter Fahrfunktionen ist die Validierung dieser Systeme. Ein möglicher Ansatz, den Validierungsaufwand zu meistern, ist der Einsatz von Simulationen. Hierbei können Simulatoren für verschiedene Aspekte des Validierungs-Prozesses verwendet werden. Um verwendbare Ergebnisse zu erhalten, müssen die einzelnen Aspekte der Realität dabei durch entsprechende Modelle abgebildet werden. Basierend auf einer Analyse verschiedener Anwendungsfälle für Simulationen, werden in diesem Beitrag verschiedene Klassen von Modellen für das menschliche Fahrverhalten hinsichtlich ihrer Anwendbarkeit im Rahmen der simulativen Absicherung evaluiert.

Schlagwörter: hoch-automatisiertes Fahren; szenario-basiertes Testen; Verifikation und Validierung.

1 Introduction

In recent years, there is an increased focus on the development of autonomous vehicles and highly automated driving functions (HAD). One of the main goals when introducing such systems is improving general road safety by reducing the number of accidents.

Today's driving functions are mainly safeguarded using test drives. The main focus of these tests is the validation of the electrical and mechanical systems of the vehicle. Especially, no testing effort concerning the interaction between the vehicle and other traffic participants is required, as the decision making and actual control of the car is the responsibility of the driver.

Unfortunately, the short-cut, of defining the task of decision making as outside the scope of the validation process, is no longer possible for vehicles equipped with highly-automated driving functions. A common architecture for decision making systems in complex and changing environments is the sense-plan-act paradigm [1, chapter 12]. While originating from the field of robotics this approach is also often used for highly-automated driving functions. Compared to conventional vehicles, functionality for perception of the environment as well as other traffic participants and decision making systems determining the vehicles future motion are added. Therefore, additional testing is required to verify the functionality of the perception as well as the planning and execution algorithms.

In order to evaluate the performance of these components, especially the planning algorithms, the behavior

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of the vehicle in traffic must be verified. As indicated in Figure 1, the behavior of the highly-automated vehicle is dependent on the environment, which is also influenced by other traffic participants. Thus the other participants need to be taken into account when assessing the behavior of the highly-automated driving function under test. In theory, the decision making must be evaluated for all possible combinations of traffic participants and their behaviors, which leads to a number of combinations that is impossible to handle.

To generate more specific numbers, it is assumed that the approval of highly-automated driving function requires that these do not produce more errors than human drivers. Statistical studies in [2] show that more than 120 million test kilometers are required for the approval of highly automated systems by means of test drives. An investigation with other methods in [3] comes to similar results. Since validation has to take place for each product iteration, this procedure is not practicable due to the high time investment and, with average costs of 2.65 €/km [2], it is also not economical. Therefore, current research activities, such as the Pegasus project and its successors [4], deal with the search for alternative validation methods.

A possible alternative to test drives is the usage of simulation technology in the validation process. A promising approach is the concept of scenario-based testing [5], as it breaks down the testing effort into scenarios rated as relevant, that can be tested specifically. This is particularly interesting for situations that only rarely occur in reality or can only be tested with considerable additional effort due to a high level of risk.

The general idea of scenario-based testing is, that the validation effort can be broken down in a (finite) set of relevant scenarios. A simplified overview of the underlying process chain presented in [5] can be found in Figure 2. In the first step, the scenarios relevant for the validation must be identified. Based on these scenarios, test cases can be derived. To perform the actual evaluation, these test cases are executed using different testing methods like software-in-the-loop, hardware-in-the-loop and non-simulative tests on proving grounds. In the following, only the identification of relevant scenarios and the simulation-based test execution will be discussed. This article does not deal with test case generation, as this step is executed without the use of simulation. Additionally, non-simulative testing methods, such as tests on proving grounds or in real traffic, will not be explained.

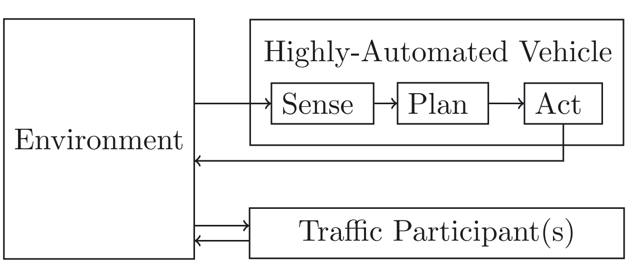

Figure 1: Overall system model of traffic including highly-automated vehicles and traffic participants.

The focus of this contribution is on those aspects of scenario-based testing that are influenced by models for traffic participants. Other aspects, such as the evaluation of scenarios and test runs as well as scenario variation procedures, are not considered here. An overview of the state of the art on these aspects can be found in [6].

While simulations are an effective tool to reduce costs and effort compared to test drives, results created by simulation are only useable if they correctly represent real-world behavior. In the context of validating the behavior of a highly-automated driving functions, this means that the behavior of the other traffic participants has to be modeled correctly, as the results of the simulation can not be used to deduce sound arguments otherwise. Due to this necessity, a major task in the development of simulation tools is the creation of traffic participant models capable of correctly representing real world behavior. Therefore, a central focus of this contribution is on traffic participant models used in the simulations for validation purposes.

The remainder of this paper is structured as follows: In Section 2 the simulation tasks are introduced and a description of the needed simulation technology is given. Based on this, requirements for the models used are derived in Section 3.1 for the respective simulation tasks. In Section 3.2 various model classes from the state of the art are presented and evaluated with regard to the stated requirements. Finally, Section 3.3 analyses the suitability of the models for the usage in the respective application cases.

2 Application of simulation in testing

In order to leverage the advantages of scenario-based testing, simulation technologies can be used in order to

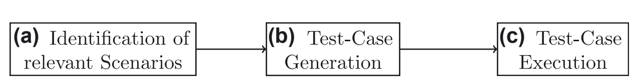

Figure 2: Process chain for the approval of highly automated driving function, consisting of the identification of relevant scenarios, test case generation and subsequent test execution.

simplify the tasks of identifying relevant scenarios and test case execution compared to the manual definition of scenarios be tested based on recorded data or system knowledge and the complex execution of test cases on proofing grounds respectively. The resulting simulation tasks, are discussed in more detail in subsection 2.1.

Based on the properties of the simulation tasks under consideration an overview over simulation technologies is presented in subsection 2.2, deducing the need for traffic participant models.

2.1 Simulation tasks

Based on the process chain of scenario-based testing presented in Figure 2, two different simulations tasks can be defined. As these two tasks are fundamentally different, resulting in deviating requirements, they will be discussed in the following in more detail.

2.1.1 Identification of relevant scenarios

The aim of identifying relevant scenarios is to find scenarios that are classified as critical and must therefore be specifically examined during validation. This step must therefore cover scenarios that are critical due to the interaction with other traffic participants, as well as critical scenarios caused by possible defects and shortcomings of the deployed systems, hardware and technology. As the second type of relevant scenarios are caused by the components of the vehicle itself and can be covered using traditional testing method, only procedures for the identification of scenarios relevant due to the interaction with other traffic participants are considered in the following.

In general, relevant traffic scenarios can be identified by evaluating recorded data or data generated by simulation. Other types of relevant scenarios can be identified through knowledge-based methods. However, only simulative approaches will be considered in this work.

A possible approach for the simulative determination of relevant scenarios is the usage of long running simulations with randomly generated traffic participants or the simulation of large quantities of scenarios using different initial values and parametrizations for the same basis scenario. A method for using a combination of traffic simulators and Monte Carlo simulations to generate test data is for example proposed in [7].

The main advantage of simulative data generation is the low time required compared to recording real data. With a purely simulative approach, however, there is a risk of incomplete coverage of the scenario space spanned by the real traffic situation due to aspects of the traffic situation that are either not modeled or unknown. A concept for a system architecture using a combination of real-world data and simulation is presented in [8].

2.1.2 Test-case execution

In the next step, the scenarios identified as relevant, can be used to test the highly-automated driving function under consideration. The tests can either target specific components or the behavior of the overall system. When performing component tests, the focus of the simulation is on the component to be tested. Therefore, the simulation of other road users plays only a subordinate role. For testing the overall behavior, however, the behavior of other participants is a central part of the simulation environment.

The essential task for the validation of highly-automated driving functions is to ensure that no unacceptable risk is caused by these systems. In order to evaluate the performance of the deployed systems, simulation environments capable of simulating realistic behavior and decision making for other traffic participants are required.

2.2 Simulation technologies

In order to carry out the simulations tasks presented in subsection 2.1, suitable simulation technologies are needed. In general, two general simulation setups for verification are distinguished in literature: On the one hand, there are simulations incorporated into a driving vehicle evaluating in the performance of a device under test online. On the other hand, simulation technology can be used in a software-in-the loop environment testing the algorithms of the highly-automated driving functions in either an open-loop or a closed-loop setup.

2.2.1 Passive highly-automated driving

While pure simulation based testing can be used to overcome the problem of the large amount of test-kilometers the validity of the results is generally questionable. Therefore [9], proposes the combination of virtual assessment via simulation and real-world driving. Based on these conceptual ideas, the *passive highly-automated driving* approach is presented in [10] to counteract the problems caused by the large amount of test kilometers. The basic idea is based on the installation of a, so-called, passive highly-automated driving function. The applied function features the full functionality to be tested and is therefore able to constantly apply the decision algorithm to be tested.

Nevertheless the calculated actions are not used to control the vehicle itself, which is still controlled by a human driver. Instead, an internal simulation, deployed to the vehicle, is used to simulate the calculated actions of the driving functions in a virtual representation of the real-world situation at hand. These simulation results can then be used to test the driving functions, by checking if the theoretical behavior of the driving function is classified as critical. In this case the data for the corresponding scenario is recorded and fed back to the development process.

While this strategy allows the testing of highly-automated driving functions in real traffic, by distributing the testing effort to multiple vehicles, passive highly-automated driving has its limitations. One of the main disadvantages is that, over time, deviating actions between the driver and the driving function lead to a discrepancy between the simulated world and what is actually happening. While this is not a problem on a short time horizon, a suitable method to re-map the simulated environment to the real-world scenario is needed.

Additionally, it is required to equip the vehicle with sensors, computing units and software for the driving function to be tested as well as the simulation environment needed to perform the evaluation of the calculated actions. As these components are needed for the evaluation process only, no actual added value for the vehicles owner and occupants is gained. The approach is therefore cost-intensive when used in a large-scale fleet operation. Additional questions and complications arise from the need to retrieve the data recorded as relevant as well as the need to update the deployed functions if an updated version is available.

2.2.2 Open-loop vs. closed-loop simulation

All approaches presented so far, have in common that a suitable simulation environment needs to be constructed in order to execute the simulation task itself. The most naive form of a simulation environment, which is based on the replay of recorded data from other traffic participants, is presented in [11]. A major issue of this approach is, that the behavior of the simulated traffic participants is solely created by replaying recorded data, neglecting the effect, that the actual behavior of a traffic participant depends on the current situation. However, in simulation the situation is altered by introducing the vehicle under test into the scenario, resulting in a deviation between the behavior represented by the recorded data, and the actual behavior of a human driver in the simulated scenario.

To overcome this problem, closed-loop simulations can be used to make the simulation independent of recorded data. In contrary to open-loop simulations using predefined behaviors for traffic participants, closed-loop simulations benefit from online generation of behaviors based on the current world state. While open-loop simulations can be useful in simulation based testing of individual components, they are not suitable for testing motion prediction algorithms. Especially, if the interaction between the highly-automated driving functions and other traffic participants shall be tested, a closed-loop simulation using dedicated traffic participant models is needed. The resulting (simplified) simulation architecture, assuming a human driven car as traffic participant, can be seen in Figure 3. The architecture of the traffic participant model, will be presented in Section 3 in more detail.

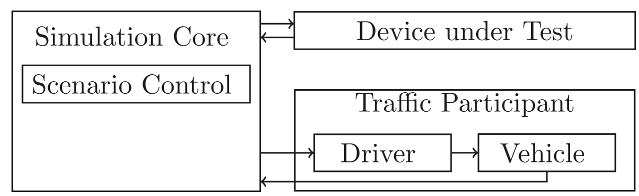

Figure 3: Simplified simulation architecture for closed-loop simulation using traffic participant models.

Therefore, an overview of the state of the art is given in the following section. The analysis is thereby limited to models for human driving behavior. Other types of road users such as pedestrians or cyclists are not considered.

3 Traffic-participant models

Over the years a great variety of models for human driving behavior have been introduced in literature for different applications. In the following, the various resulting model classes are presented and evaluated with regard to their suitability for the different simulation tasks presented in Section 2.1.

In order to do so, requirements for the models are formulated as a first step in Section 3.1. Based on this, Section 3.2 introduces the essential model classes and evaluates them with respect to the deduced requirements. As different simulation tasks put varying emphasis to the requirement, Section 3.3 assesses the suitability of the model classes for the respective simulation tasks.

3.1 Requirements

The simulation tasks presented in Section 2.1, have different requirements for the simulations and thus for the used models.

A general requirement, relevant in all applications using model-based techniques, is choosing the correct abstraction level for modeling. As testing of highly-automated driving functions is mainly concerned with the behavior of the vehicle in traffic, the traffic participants models used, must be able to describe the behavior of a single traffic participant, ruling out models unable to do so.

For long-term simulation runs, which are used to identify relevant scenarios (Figure 2(a)), a high execution speed is required, as similar to validation by means of test drives, a large number of simulated kilometers and/or scenarios is required, in order to be able to form sufficient confidence about the completeness of the relevant scenarios. Considering a minimum of $d = 120 \cdot 10^6$ km, as calculated in [2], and an average velocity of $v = 50$ km/h, $T = 2,4 \cdot 10^6$ h of simulation time are needed, if the simulation is run using real-time capable models. Even if parallel execution of simulations for different scenarios are considered it can be seen, that models with faster-than-real-time capability are needed. In the same setup as before, using a model capable of running 10 times faster than real time and 100 parallel simulation sessions would significantly shorten the simulation time to $T = 2400$ h, which is equivalent to roughly 14 weeks. While these numbers are rough estimates, they clearly emphasis the necessity of high-execution speeds.

Since test cases are only generated for the scenarios identified as relevant, the duration of the necessary simulations (Figure 2(c)) is significantly shorter compared to the long-term simulation runs. Therefore, the execution speed of the models only plays a subordinate role. In order to be able to use the simulation results in the validation process, however, it is crucial that the simulated behavior of other road users corresponds to the real behavior. Therefore, the generated behavior needs to be as accurate as possible.

An additional requirement, which is relevant for both simulation tasks, is the ability of the model to generate a large scenario space by simple changes of model parameters. In particular, it must be possible to create scenarios that either only rarely occur in reality or can not be implemented on testing grounds with reasonable effort, due to high risk.

Summing up, this results in the following requirements for the traffic participant models used in the simulation:

- Abstraction Level: Models must be able to describe the behavior of individual traffic participants.
- Execution Speed: Short simulation time compared to simulated time.
- Accuracy: Correct representation of real human driving behavior.
- Generalizability: Capability to generate a variety of scenarios.
- Parameterability: Suitable tuning parameters for the creation of different scenarios.

Additionally it can be seen, that, due to the different goals of the simulation tasks under consideration, the importance of the requirements varies between the individual tasks. While the identification of relevant scenarios has a high emphasis on execution speed as well as parameterability and generalizability, accuracy of the simulated behavior is of less relevance. On the other hand, for the execution of test cases accurate models that can be easy parameterized are needed. An overview of the relevance of the requirements for the individual tasks is presented in Table 1.

3.2 Evaluation of the model classes

In the following section, different model classes for modeling human driving behavior will be discussed and analyzed with regard to their suitability for simulative validation, based on the requirements stated in Section 3.1.

Table 1: Importance of requirements for individual simulation tasks, whereby +/− imply high/low significance respectively.

	Relevant scenario identification	**Test case simulation**
Abstraction level	+	+
Execution speed	+	−
Accuracy	−	+
Generali-zability	+	+
Parameter-ability	+	+

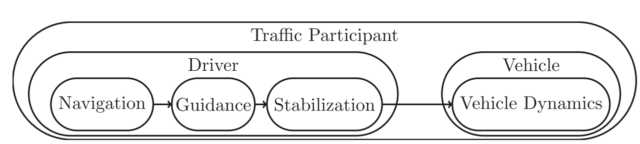

Figure 4: Overall model of a traffic participants consisting of a vehicle and a human driver. The driver can thereby be modeled using the 3-layer model from [12].

As shown in Figure 4, a model of a traffic participant consists of a model for the driver and a model for the vehicle dynamics. According to [12], human driving behavior can be divided into the three levels "navigation", "guidance" and "stabilization". The navigation level, modeling the search for a suitable route, is not considered in simulative testing applications, assuming that the route to be traveled is given by an external specification (e.g. scenario or test case description). In contrast, the levels guidance and stabilization reflect the driver's tactical decision-making and vehicle control inputs.

In literature, the term "driver-model" is used ambiguous. On the one hand, models for the overall behavior of complete traffic participants are called driver models. These models directly calculate vehicle states (like position, orientation and the respective velocities) with respect to the world-frame of the simulation. On the other hand, there are models describing the human driver exclusively. Typical outputs of these models are desired velocity and desired orientation when modeling the guidance level or pedal position when modeling the stabilization, respectively. In the context of simulation based testing, models describing the complete traffic participant are needed. Note however, that this does not disqualify models describing the human driver, as they can in general be extended to traffic participant models by combining them with suitable vehicle dynamic models.

In the remainder of this section, various model classes for traffic participant models are presented. An overview over these model classes is given in Figure 5.

3.2.1 Traffic-flow models

One of the categories of traffic participant models are traffic flow models, originally developed to assist in the design of traffic infrastructure [13]. According to [14], these can be further subdivided into microscopic and macroscopic models. An overview of different models of both types can be found in [14].

In general, macroscopic models cover statistical properties of traffic flow using partial derivative equations to determine vehicle densities, traffic volumes and average velocity dependent on position and time. Due to their nature, these models do not give any insight into the behavior of a single traffic participant, rendering them unsuitable for the identification of relevant scenarios (Figure 2(a)) as well as the simulation of test cases (Figure 2(c)).

On the other hand, microscopic traffic flow models (MiTFM) depict traffic flow by explicitly modeling the behavior of individual road users, whereby the level of detail reaches from simple cellular automata to more sophisticated car-following and physio-psychological methods. While the original aim behind the development of traffic flow models has been the statistical analyses of traffic flow, microscopic models additionally generate trajectories representing the behavior of individual traffic participants. Nevertheless, their ability to create a realistic representation of real human behavior is limited, reducing their usability in applications with high requirements concerning realism of simulated trajectories. However, due to the simplicity of these models, computational complexity and computation times are significantly reduced, compared to other model types.

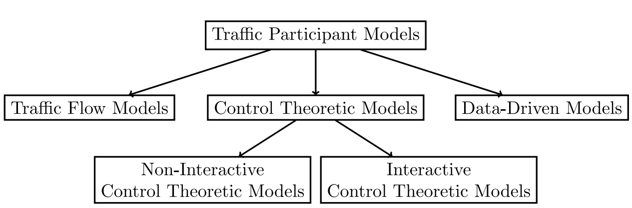

Figure 5: Overview over the most relevant classes of traffic participant models.

3.2.2 Data-driven models

A commonly used modeling approach is the use of purely data-driven models (DDM), based on machine learning techniques including fuzzy systems [15], neural networks [16], reinforcement learning [17] or hidden Markov models [18]. Additional, data-driven models based on auto-regressive systems have been introduced for various uses cases [19]. Concerning the three-layer model in Figure 4, most data-driven models can be allocated to the stabilization and guidance layer.

These models can be used to easily create a representation of recorded data without having to rely on a-prior system knowledge. A major advantage of data-driven modeling compared to alternative approaches, is that efficient methods for identifying the model parameters based on a recorded data set are readily available. Therefore, these types of models are often used for (online) identification of a drivers current behavior [19].

Although data-driven models are in general able to correctly reproduce human driving behavior, they are only suitable to a limited extent for simulating test cases (Figure 2(c)). On the one hand, purely data-driven models have only limited capability to describe behaviors that rarely occur or do not exist in the training data. Here again, to obtain a sufficient amount of training data, an impractical amount of data must be recorded. On the other hand, these models can not be easily parameterized to create different variations of behavior/scenarios.

3.2.3 Control theory based models

In order to generate models with better parameterization capabilities, control theory based traffic participant models (CTM) can be used [20] for modeling. In contrast to data-driven models, which can only represent the input/output behavior, models based on control theoretic methods are able to specifically model individual effects that influence human driving behavior. Based on the consideration of other traffic participants, two different kinds of control theory based models can be distinguished:

- Non-Interactive CTMs: The influence of the own behavior on the behavior of other traffic participants is neglected.
- Interactive CTMs: These models explicitly model the interaction between traffic participants.

Typical examples for effects explicitly modeled using non-interactive control theoretic methods are human preview as well as reaction time. A model considering both effects for a longitudinal control model at the same time is presented in [21] using (a-causal) delay-time elements to model preview and reaction time respectively. While [21] combines control-theoretic methods with neural networks, [22] introduces a purely control-theoretic approach based on explicit modeling of preview and control for driver steering behavior. Another common way to model the capability of preview is the usage of model-predictive controllers as, for example, presented in [23]. Essentially addressing the human longitudinal and/or lateral control behavior, all three models can be located on the stabilization level.

A completely different approach modeling the limitations of perception, decision making and execution is presented in [24]. Hereby, the human perception and its limitation are modeled using queuing theory, while an automata is used for the modeling of human decision making. Finally, a longitudinal and lateral controller are used to calculate the acceleration outputs based on the velocities selected via the automata. In contrary to the models presented in the paragraph before this model not only considers stabilization but also the guidance layer.

By parameterizing the individual effects, different behaviors and various scenarios can be generated in a targeted manner. The number of scenarios that can be generated using these models depends heavily on the modeled effects.

A disadvantage of non-interactive control theoretic modeling approaches is that there is no explicit modeling of the interaction between different road users. However, in many scenarios, such as lane changing on multi-lane roads or at intersections, interaction between drivers of different vehicles has a significant impact on driving behavior. One method for the explicit modeling of interaction, which is widespread in different fields of application, is the concept of game theory. In the context of traffic participant modeling, game theory has been used for a variety of modeling task ranging from simple models for speed-selection, over behavior models for interactive scenarios like merging and intersections to traffic-flow related questions like choosing departure time to avoid traffic congestion [25].

One of the simplest game-theoretic model forms are matrix games, modeling an interaction with a single decision-making step. A major disadvantage of matrix-games is, that (possible) future consequences of the decision are not considered in the decision making. Nevertheless, there are a variety of matrix-game based models for lane change and merging [26, 27] as well as intersection scenarios [28] available in literature. In order to overcome the limitations of the matrix games [27, 28] use repeated games constructing a new game in each decision making step.

An extension of simple games to multiple decision-making steps are the so-called dynamic games. In analogy to optimal control theory, the coupled optimization problems lead to coupled differential/difference equations. A major drawback of dynamic games is the high computational effort attached to solving the coupled optimization problems. One way to limit the computational effort, is the reduction of the decision making to a finite action space. In the context of driver decision making this can be done by partitioning the movement of the traffic participants into so-called maneuvers. The use of maneuvers is thereby not limited to game-theoretic models as it is also used in control-theoretic [24] as well as data-driven [18] modeling approaches.

Examples of the use of dynamic games for traffic participant models can be found in [29–32]. The models in [29] use *level-k* game-theory to select the acceleration and yaw rate of the traffic agent in an intersection scenario from a predefined set of maneuvers. The maneuvers are thereby modeled using discrete values limiting the degree of realism.

In [31], this model is compared to a game-theoretic model, for the multi-vehicle interaction in an intersection scenario. Analogously, the acceleration is selected from a finite set of discrete acceleration values. In contrary, it is assumed that the path of the vehicle is given by the lane topology of the intersection. The increased computational load is counteracted by using a pairwise, Stackelberg inspired, solution strategy. For each pair of players the leader and the follower is determined resulting in a Stackelberg game with two players. Lastly, the results from all Stackelberg games a player is involved in, are fused to determine the actual strategy of the player.

A different approach for a game-theoretic driver decision making model in an intersection scenario is presented in [32]. While it is assumed, that the players follow a predefined path, the maneuvers used to calculate the acceleration are modeled based on the Intelligent Driver Model (IDM) [33]. Hereby, the selection of a more sophisticated maneuver model is used to create a more realistic velocity profile of the simulated traffic participant without increasing the computational complexity. Additionally, a hybrid system approach based on an automata is used to model further restrictions on the maneuver switching, defining a set of possible following maneuvers based on the current one.

Lastly, the model in [30] uses a *level-k* game-theory approach to model a lane change scenario. Again a limited set of acceleration values is used as a maneuver model. In contrary to the game-theoretic models presented so far, the model in [30] uses a reinforcement learning approach to solve the game-theoretic problem modeling the drivers decision making.

In general, it can be seen that the main focus of most game-theoretic models, is the selection of maneuvers. Therefore, these models mostly address the task of guiding the vehicle. Additional, motion models for the maneuvers are used to describe the kinematic behavior of the vehicle. Compared to non-interactive models these motion models are simplified, often combining stabilization and vehicle dynamics into a simplified kinematic motion model. The extent to which game-theoretic models are suitable for generating different scenarios through parameterization depends largely on the chosen solution method. While [30] uses a solution based on reinforcement learning, [32] uses an algorithm directly solving the game-theoretic problem at execution time. The latter allows easy modification of the model parameters to generate different scenarios.

A summery over the properties of the various model classes presented in this section is given in Table 2. Additional it can be noted that all model classes presented in Table 2 are able to describe the behavior of an individual traffic participant fulfilling the abstraction level requirement.

3.3 Suitability for simulation tasks

Due the varying importance of the individual requirements for the different simulation tasks, the suitability of different models, also varies. Therefore, based on the requirements specified in Section 3.1 and the model properties discussed in Section 3.2, the different model classes need to be assessed concerning their suitability for the individual simulations tasks.

Using these results, the usability of the models for the relevant use-cases can be assessed based on the importance of the different requirements for the respective use-cases.

As described in Section 3.1, the identification of relevant scenarios uses long-running simulations. Therefore, the most important requirements are a high-execution speed combined with the capability to create a wide variety of scenarios. On the other hand, the closeness to reality of the generated simulation results is of less significance.

Therefore, microscopic traffic flow models are suitable for the task at hand. For example [8], analyzes the applicability of the traffic flow simulators SUMO [34] and PTV Vissim [35] for scenario generation, which is one of the key steps in creating the vast amount of scenarios needed in the identification step. While both simulators showed promising results, it was found that their ability to recreate the trajectory-variance that can be observed in urban-scenarios is limited.

Control-theoretic models are in general also suitable for this simulation use-case due to their easy parameterability and ability to create a wide variety of scenarios. However, only models with low computational loads can be used, ruling out more complex models, like, for example, those based on optimal control or game-theory.

In contrary, simulation-based test execution has a stronger emphasis on the detailed and realistic simulation of individual scenarios. Additionally, models with high generalizability and parameterability are needed in order to simplify scenario setups, based on the test-case description. Therefore, control-theoretic traffic participant models are the best choice for this simulation use-case. Simple examples for the usage of game-theoretic models to evaluate driving function in a lane change and intersection setup are presented in [29, 30], respectively. While the presented examples show promising results, further model improvements are needed. Especially, it is unclear whether the accuracy of existing models suffices for simulation based testing applications. While plausibility checks based on data, statistics and expert knowledge exist for most models, extensive reviews of the model accuracy needs to be conducted.

Table 2: Comparison of microscopic traffic flow models (MiTFM), data driven models (DDM) and control theoretic models (CTM).

	MiTFM	DDM	CTM
Execution speed	Faster-than-real-time	Real-time	(Partially) real-time
Accuracy	Accurate for statistical properties	Accurate within training data	Accurate for modeled effects
Generalizability	Model-dependent	Only within training data	Within modeled effects
Parameter-ability	High-parameter count	No behavior adjustment	Easy parameterizable

From the presented examples it can be seen that the suitability of a specific model for a given test-case or scenario must be evaluated individually, based on the modeled effects and the requirements deduced from the test-specification. As an example, the model in [32] only considers effects relevant for the decision making in intersection scenarios. Therefore, this model could be used for the evaluation of decision-making algorithms in intersection scenarios but would not be suitable for the testing of a lane-change system.

On the other hand, purely data-driven models can be used in this application to some extent. As before, in the selection of an appropriate model for the simulation task at hand it is important to select a model that is able to describe the behaviors relevant for the scenario to be simulated. While the models are able to create scenarios useful for the validation of highly-automated vehicles their non-parameterability results in an increased effort, to create the specific scenarios described in a given test case.

Additionally, the usability of microscopic traffic flow models is limited to test cases, not requiring highly realistic representations of individual driver behavior. An example, where microscopic traffic flow models can be used, is the testing of vehicle-to-vehicle or vehicle-to-infrastructure components [36].

Finally, it should be noted that only deterministic models are suitable for the validation task, as it is important that identical initial conditions and parametrizations of models always lead to identical simulation results. Otherwise, no test result meaningful to the validation effort can be created.

Table 3: Evaluation of model classes for the individual use cases.

	Relevant scenario identification	Test case simulation
MiFTM	+	−
DDM	−	o
CTM	o	+

To summarize the results of this chapter, Table 3 gives an overview of the suitability of the model classes under consideration for the relevant simulation tasks. In general, it can be said, that microscopic traffic flow models can mainly be used for the identification of relevant scenarios, but are unsuited for test execution due to their comparatively low accuracy in individual scenarios. On the other hand, control theoretic models are well suited for the simulation of individual scenarios. While they can, in theory, be used for the identification of relevant scenarios, their high execution times is usually at odds with this simulation task. Lastly, data driven models on the other hand, while useable in some niche use cases, are mostly unsuited for simulation based testing environments.

4 Conclusions

This paper focuses on the extent to which simulations can be used to validate highly automated driving. In particular, the identification of relevant test scenarios and the simulation of individual test cases are explained in more detail. Based on these two use cases, different traffic agent models are evaluated with regard to their suitability for the respective simulation tasks.

While the presented analysis gives an initial draft for a model selection guideline, further research needs to be done into formulating more definite and quantifiable requirements for the various simulation tasks. Based on these requirements the traffic participant models available in the state of the art need to be individually evaluated concerning usability and needed improvements.

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References

[1] B. Siciliano and O. Khatib, *Springer Handbook of Robotics*, Cham, Springer International Publishing, 2016.
[2] W. H. K. Wachenfeld, "How stochastic can help to introduce automated driving," dissertation, Darmstadt: Technische Universität Darmstadt, 2016.
[3] N. Kalra and S. M. Paddock, "Driving to safety: how many miles of driving would it take to demonstrate autonomous vehicle reliability?" in *Driving to Safety. How Many Miles of Driving Would It Take to Demonstrate Autonomous Vehicle Reliability?* RAND Corporation, pp. 1–16, 2016. Available at: http://www.jstor.org/stable/10.7249/j.ctt1btc0xw.1.
[4] Pegasus, *Pegasus Project Family*. Available at: https://pegasus-family.de/ [accessed: Aug. 18, 2022].
[5] C. Neurohr, L. Westhofen, T. Henning, et al., "Fundamental considerations around scenario-based testing for automated driving," in *2020 IEEE Intelligent Vehicles Symposium (IV)*, IEEE, 2020, pp. 121–127.
[6] Z. Zhong, Y. Tang, Y. Zhou, et al., *A Survey on Scenario-Based Testing for Automated Driving Systems in High-Fidelity Simulation*, 2021, https://arxiv.org/pdf/2112.00964.
[7] T. Helmer, L. Wang, K. Kompass, et al., "Safety performance assessment of assisted and automated driving by virtual experiments: stochastic microscopic traffic simulation as knowledge synthesis," in *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, IEEE, 15.09.2015 – 18.09.2015, Lehrstuhl für Fahrzeugtechnik, Technische Universität München, 2015, pp. 2019–2023.
[8] N. Weber, C. Thiem, and U. Konigorski, *A Needle in a Haystack – How to Derive Relevant Scenarios for Testing Automated Driving Systems in Urban Areas*, 2021. Available at: https://arxiv.org/pdf/2109.03648.
[9] W. H. K. Wachenfeld and H. Winner, "Virtual assessment of automation in field operation: a new runtime validation," in *10. Workhsop Fahrerassitenzsysteme*, 2015, pp. 161–170.
[10] A. Koenig, M. Gutbrod, S. Hohmann, et al., "Bridging the gap between open loop tests and statistical validation for highly automated driving," *SAE Int. J. Transp. Saf.*, vol. 5, no. 1, pp. 81–87, 2017.
[11] J. Bach, K. L. Bauer, M. Holzäpfel, et al., "Control based driving assistance fucntions' test using recorded in field data," in *7. Tagung Fahrerassistenzsysteme*, München, Lehrstuhl für Fahrzeugtechnik, Technische Universität München, 2015.
[12] E. Donges, "A conceptual framework for active safety in road traffic," *Veh. Syst. Dyn.*, vol. 32, nos. 2–3, pp. 113–128, 1999.
[13] D. Helbing, *Verkehrsdynamik: Neue Physikalische Modellierungskonzepte*, Berlin, Heidelberg, Springer Berlin Heidelberg, 1997.
[14] S. Krauß, "Mircroscopic modeling of traffic flow: investigation of collision free vehicle dynamics," dissertation, Köln: Universität Köln, 1998.
[15] A. El Hajjaji and M. Ouladsine, "Modeling Human Vehicle Driving by fuzzy logic for standardized ISO double lane change maneuver," in *ROMAN 2001*, Piscataway, N.J., IEEE, 2001, pp. 499–503.
[16] N. Kehtarnavaz and W. Sohn, "Steering control of autonomous vehicles by neural networks," in *American Control Conference*, IEEE, 1991, 6/26/1991 – 6/28/1991, pp. 3096–3101.
[17] Y. Jiang, W. Deng, J. Wang, et al., "Studies on drivers' driving styles based on inverse reinforcement learning," in *WCX World Congress Experience. SAE Technical Paper Series*, Warrendale, PA, United States, SAE International, 400 Commonwealth Drive, 2018.
[18] J. Inga, M. Flad, G. Diehm, and S. Hohmann, "Gray-box driver modeling and prediction: benefits of steering primitives," in *2015 IEEE International Conference on Systems, Man, and Cybernetics*, IEEE, 2015, pp. 3054–3059.
[19] W. Wang, J. Xi, and H. Chen, "Modeling and recognizing driver behavior based on driving data: a survey," *Math. Probl. Eng.*, vol. 1, pp. 1–20, 2014.
[20] C. C. Macadam, "Understanding and modeling the human driver," *Veh. Syst. Dyn.*, vol. 40, nos. 1–3, pp. 101–134, 2003.
[21] J. Cao, H. Lu, K. Guopg, et al., "A driver modeling based on the preview-follower theory and the jerky dynamics," *Math. Probl. Eng.*, vol. 1, pp. 1–10, 2013.
[22] R. A. Hess and A. Modjtahedzadeh, "A preview control model of driver steering behavior," in *Conference Proceedings., IEEE International Conference on Systems, Man and Cybernetics*, IEEE, 1989, pp. 504–509.
[23] H. Y. Guo, Y. Ji, T. Qu, et al., "Understanding and modeling the human driver behavior based on MPC," *IFAC Proc. Vol.*, vol. 46, no. 21, pp. 133–138, 2013.
[24] U. Kiencke, R. Majjad, and S. Kramer, "Modeling and performance analysis of a hybrid driver model," *Control Eng. Pract.*, vol. 7, no. 8, pp. 985–991, 1999.
[25] R. Elvik, "A review of game-theoretic models of road user behaviour," *Accid. Anal. Prev.*, vol. 62, pp. 388–396, 2014.
[26] K. Kang and A. H. Rakha, "Game theoretical approach to model decision making for merging maneuvers at freeway on-ramps," *Transp. Res. Rec.: J. Transp. Res. Board*, vol. 2623, no. 1, pp. 19–28, 2017.
[27] K. Kang and A. H. Rakha, "Modeling driver merging behavior: a repeated game theoretical approach," *Transp. Res. Rec.: J. Transp. Res. Board*, vol. 14, no. 4, pp. 144–153, 2018.
[28] R. Mandiau, A. Champion, J. M. Auberlet, et al., "Behaviour based on decision matrices for a coordination between agents in a urban traffic simulation," *Appl. Intell.*, vol. 28, no. 2, pp. 121–138, 2008.
[29] N. Li, I. Kolmanovsky, A. Girard, et al., "Game theoretic modeling of driver and vehicle interactions for verification and validation of autonomous vehicle control systems," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 5, pp. 1782–1797, 2018.
[30] N. Li, I. Kolmanovsky, A. Girard, et al., "Game theoretic modeling of vehicle interactions at unsignalized intersections and application to autonomous vehicle control," in *2018 Annual American Control Conference (ACC)*, IEEE, 6/27/2018 – 6/29/2018, 2018, pp. 3215–3220.

[31] N. Li, Y. Yao, I. Kolmanovsky, et al., "Game-theoretic modeling of multi-vehicle interactions at uncontrolled intersections," in *IEEE Transactions on Intelligent Transportation Systems*, IEEE, 2020, pp. 1–15.
[32] M. Lemmer, J. Shu, S. Schwab, et al., "Maneuver based modeling of driver decision making using game-theoretic planning," in *2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, IEEE, 2021, pp. 1332–1338.
[33] H. Treiber and Helbing, "Congested traffic states in empirical observations and microscopic simulations," *Phys. Rev. E*, vol. 62, no. 2 Pt A, pp. 1805–1824, 2000.
[34] P. A. Lopez, M. Behrisch, L. Bieker-Walz, et al., "Microscopic traffic simulation using SUMO," in *2018 IEEE Intelligent Transportation Systems Conference*, Piscataway, NJ, IEEE, 2018, pp. 2575–2582.
[35] PTV Group, *PTV Vissim*. Available at: https://www.ptvgroup.com/de/loesungen/produkte/ptv-vissim/ [accessed: Aug. 28, 2022].
[36] T. Otto and R. Hoyer, "Devices-in-the-Loop approach – traffic simulation meets real devices of distributed V2I applications," in *Mobil.TUM 2009 – International Scientific Conference on Mobility and Transport*, Ed. by Technische Universität München, 2009.

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