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Modeling Automated Driving in Microscopic Traffic Simulations for Traffic Performance Evaluations: Aspects to Consider and State of the Practice

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***Abstract*— The gradual deployment of automated vehicles on the existing road network will lead to a long transition period in which vehicles at different driving automation levels and capabilities will share the road with human driven vehicles, resulting into what is known as mixed traffic. Whether our road infrastructure is ready to safely and efficiently accommodate this mixed traffic remains a knowledge gap. Microscopic traffic simulation provides a proactive approach for assessing these implications. However, differences in assumptions regarding modeling automated driving in current simulation studies, and the use of different terminology make it difficult to compare the results of these studies. Therefore, the aim of this study is to specify the aspects to consider for modeling automated driving in microscopic traffic simulations using harmonized concepts, to investigate how both empirical studies and microscopic traffic simulation studies on automated driving have considered the proposed aspects, and to identify the state of the practice and the research needs to further improve the modeling of automated driving. Six important aspects were identified: the role of authorities, the role of users, the vehicle system, the perception of surroundings based on the vehicle's sensors, the vehicle connectivity features, and the role of the infrastructure both physical and digital. The research gaps and research directions in relation to these aspects are identified and proposed, these might bring great benefits for the development of more accurate and realistic modeling of automated driving in microscopic traffic simulations.**

***Index Terms*— Microscopic traffic simulation, automated driving, automated vehicles, traffic flow performance, mixed traffic.**

I. Introduction

OVER the years, embedding of automation systems and communication technologies in automobiles has enabled them to evolve into automated vehicles. While the development towards driving automation is progressing at full speed, researchers, road operators, and the automotive industry have realized that a wide deployment of automated vehicles on existing road networks will be gradual [1], [2]. There are many reasons for this, among others, the need to have a suitable road infrastructure [3], [4], the acceptance and trust of the users of these systems [5], [6], and the need to define suitable regulations and legislation frameworks [7], [8]. A gradual deployment will result in a reality of mixed traffic consisting of vehicles at various levels of driving automation coexisting with human driven vehicles. The questions that arise are whether this mixed traffic can be safely accommodated on the existing road infrastructure, and how it would affect traffic efficiency, traffic safety, equity, and the environment.

Currently, there is limited possibility for field observations on public roads regarding the performance of automated vehicles and their effects on the traffic flow. Waiting until there are enough vehicles at different levels of driving automation operating on real roads to investigate their impact would be a reactive and unethical approach given the safety risks, and the risks of wasting significant budgets. Hence, alternative proactive approaches should be taken to assess the effects caused by the presence of automated vehicles.

Microscopic traffic simulation, henceforth also referred to as traffic simulation, provides a proactive approach for assessing the implications of mixed traffic on traffic efficiency, safety, equity, and the environment. Many studies in the literature have used traffic simulations to estimate the possible impacts of automated vehicles on traffic efficiency and safety [9], [10], [11], [12]. Nevertheless, it is difficult to compare the results from different studies due to differences in assumptions, and the use of different terminology [13], [14]. Since field observations are limited, several assumptions are made for modeling automated driving which are not always specified nor described. Terminology related to driving automation is sometimes used inconsistently and different terms related to the same concepts can be found in the literature, adding and extra dimension that complicates comparisons between studies. Thus, there is a need to identify and structure how different aspects that affect automated driving are considered in traffic simulations using well-established terminology.

The aim of this study is first to specify aspects to consider for modeling automated driving in microscopic traffic

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simulations using harmonized concepts. Empirical studies (i.e., field/road tests) on automated driving provide useful insights and data for modeling and calibration of automated driving in traffic simulation. Hence, the second aim is to investigate how both empirical, and microscopic traffic simulation studies on automated driving have considered the proposed aspects and identify the state of the practice. The third aim is to identify and highlight the research needs to further improve the modeling of automated driving. In addition, the article also aims to encourage the inclusion of a more detailed description of aspects considered in future traffic simulation studies of automated driving using harmonized concepts and definitions. It is not the intent of this paper to provide a full literature review, but rather to use the literature to identify the relevant aspects for modeling automated driving in microscopic traffic simulation for traffic performance evaluation, and the common practices and research needs in this respect.

The focus of this study is on the modeling of automated driving in traffic simulations. Although, accurate and realistic modeling of the human driving behavior is of high relevance and importance for evaluating the safety and efficiency of mixed traffic, this is not addressed in this study. For studies on the modeling human driving behavior the reader is referred to [15], [16], [17], and [18].

The remaining sections of this article are structured as follows; section II presents a list of terms and concepts used to describe the proposed aspects to consider for modeling automated driving which are presented in Section III. section IV reviews how the proposed aspects have been considered in both microscopic traffic simulation studies including automated vehicles as well as in empirical studies on automated vehicles that entail useful information, either as input for modeling or for setting up simulation experiments. In section V we discuss the state of the practice and identify the research needs. Lastly, section VI concludes the article by summarizing the main findings and research needs.

II. Terminology and Concepts

This section presents a short list of key terms and concepts used throughout this article, for a more extensive list of functional definitions and terms related to automated driving the reader is referred to [19].

Automated vehicles are assumed to have some level of connectivity ranging from simple navigation features to advanced functions for cooperative driving, in this article we use the term *automated vehicle* independently of the level of connectivity. Additionally, an *automated vehicle* refers to a vehicle capable of automated driving at any level of automation.

The Society of Automotive Engineers (SAE) defines five levels of driving automation for on-road motor vehicles [19]. The five levels differ in the capabilities of the driving automation systems to handle the different *dynamic driving tasks (DDTs)*. The DDTs are defined as all the real-time operational and tactical functions required to operate a vehicle which include the lateral and longitudinal motion controls as well as the *object and event detection and response (OEDR)*, and exclude the strategic functions such as the route selection. The driving automation systems are those that handle specific DDTs at any SAE level of driving automation (e.g., an adaptive cruise control (ACC) system), in contrast, the term *automated driving system (ADS)* refers to the system that handles *all* of the driving functions and is reserved for SAE levels 3, 4, and 5. At SAE level 1 the driver is responsible for the OEDR and for either the lateral or the longitudinal motion control of the vehicle. At SAE level 2 both the lateral and longitudinal motion controls are automated while the driver is still responsible for the OEDR. At higher levels of automation (i.e., SAE levels 3-5), the ADS is responsible for all DDTs. At SAE level 3, however, the ADS still requires the driver to monitor the OEDR and eventually take control of the vehicle. At SAE level 4, the ADS is able to safely handle all DDTs without human intervention as longs as the vehicle is cruising within its *operational design domain (ODD)*. Vehicles at all SAE levels of driving automation have a restricted ODD, except at SAE level 5. In other words, only vehicles at SAE level 5 of driving automation are capable of handling all types of situations and conditions at all times.

The *operational design domain (ODD)* is defined by the SAE as the operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics [19]. The ODD is specified by the *original equipment manufacturers (OEMs)* and describes the specific conditions under which the ADS can operate [20], [21]. Therefore, the performance of vehicles at the same SAE level of driving automation can greatly differ since it depends on the capabilities of the ADSs designed by specific OEMs. Some comprehensive lists of criteria that should be contained in the description of the ODD have been proposed in the literature [21] [22], [23].

The road infrastructure can improve the performance of the ADSs by providing additional information about the traffic and the road environment conditions. In this respect, a classification scheme with five levels of *infrastructure support for automated driving (ISAD)* has been proposed by Carreras *et al*. [3]. ISAD level E refers to the conventional infrastructure without any support for automated driving. The availability of digital maps with static regulatory information (e.g., speed limits) is assigned to ISAD level D. At ISAD level C the infrastructure provides all dynamic and static information fully digitalized. At ISAD level B the infrastructure is in addition, able to perceive detailed traffic situations through dedicated sensors and provides this information to the vehicles, enhancing their perception. At ISAD level A, the infrastructure is capable of perceiving vehicle trajectories and guiding automated vehicles individually or by groups, optimizing the overall traffic efficiency.

III. Aspects to Consider for Modeling Automated Driving

Several factors can influence how an automated vehicle performs each DDTs under specific situations. OEMs need

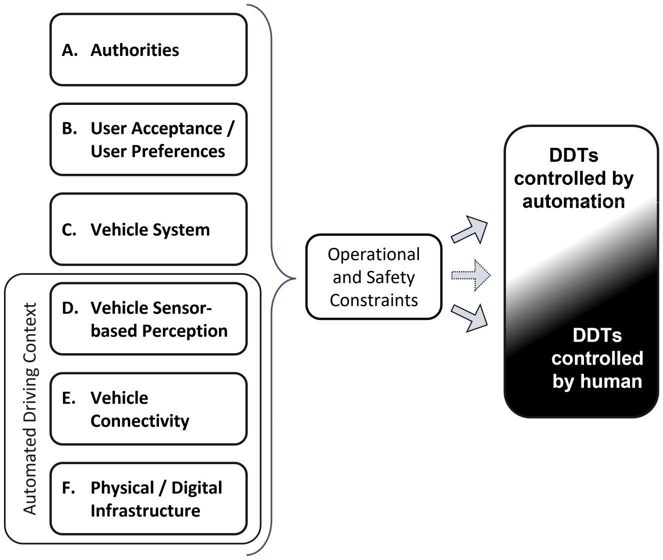

Fig. 1. Six aspects (A-F) to consider for modeling of automated driving in microscopic traffic simulation.

to take these factors into account when developing ADSs and defining the ODD of the vehicle. In traffic simulation, including all factors affecting the operation of an automated vehicle with high level of detail might not be feasible, and would be neither practical nor necessary. This approach is not unique for automated driving but applies also for the traffic simulation of human driving, for example, the interaction between the driver and the vehicle is commonly neglected, and they are considered together as a driver-vehicle unit. It is important to consider those factors that will have impacts on the traffic flow dynamics, particularly when assessing the implications on traffic efficiency and safety. Hence, as in the modeling for human driving, traffic simulation models for automated driving need to consider relevant aspects at an adequate level of detail and include a clear description of the assumptions considered.

Six aspects to consider for the modeling of automated driving in microscopic traffic simulations are identified in this article, as shown in Figure 1: the role of authorities, the role of users, the vehicle system, the perception of surroundings based on the vehicle's sensors, the connectivity features, and the role of the infrastructure both physical and digital. The last three aspects determine the interpretation of the automated driving context which comprises the information that an automated vehicle perceives about its path and its surroundings in terms of infrastructure elements, environmental conditions, fixed and moving objects (including the surrounding traffic), and the state of the driver. The automated driving context for automated vehicles is equivalent to the situational awareness for human driving. The situational awareness refers to what a driver perceives that influences their driving behavior, while the automated driving context refers to all the information an automated vehicle perceives to perform each DDT.

The six identified aspects focus on the tactical and operational levels of the driving efforts as proposed in the structure by Michon [24], and as in the definition of DDT by the SAE. Additional aspects might be needed to include the strategic driving efforts. It is important to highlight that the identified aspects are not independent from one another, and that interdependencies and overlaps between them do exist. However, addressing these interactions is out of the scope of this paper.

As shown in Figure 1, the six aspects together define the operational and safety constraints for automated driving. These constraints define if automated driving is possible for all or some of the DDTs under the current context considering the ODD. The automated driving and human driving boxes in Figure 1 represent how each DDT is handled as a result of all the considerations taken within each aspect. This can range from that all DDTs are handled by the ADS (i.e., SAE level 3 or higher) to that all DDTs are handled by the human driver and cases in which some DDTs are handled by the human and some by a driving automation system (i.e., SAE level 1-2). The range is indicated by the three arrows between the Operational and Safety constraint box and the Automated / Human Driving box in Figure 1.

With the exception of the vehicle system, the aspects are location- and situation-specific, thus, how the DDTs are handled will vary in time and space. Automated driving does not have to be static, and could dynamically change along the route depending on the conditions. The current driving context can be perceived as unsafe or can be infeasible for which a transition between driving modes (from automated driving to human driving, or vice versa) might be necessary or desirable. If automated driving is possible, the different aspects might enforce constraints for safe operation and thereby influencing the range of possible actions to handle the DDTs. These constraints can be seen as a subset of the vehicle's ODD specification. In cases outside of the ODD a transition from automated driving to human driving needs to occur, this momentary transition has its own modeling approach. The transition can be initiated either by the driver or by the ADS if the operation of the vehicle is not perceived as safe or not accepted for other reasons. At lower SAE levels of driving automation (1-3) some DDTs are handled by a human while others by a driving automation system, thus, it is possible that both human driving and automated driving take place at the same time each handling different DDTs.

Descriptions of the six aspects shown in Figure 1 are presented in more detail in the following sub-sections.

A. Authorities

This aspect considers the laws, policies and norms that regulate automated vehicles. These regulations could be as explicit as restricting automated driving to certain areas or certain lanes (i.e., geofencing the ODD), they could also be detailed about how automated driving should take place, for example, by restricting the maximum speed, the minimum distances between vehicles, etc. Laws assigning responsibilities to the OEMs and to the drivers could influence the operation of automated vehicles as well as the compliance of location-specific traffic regulations, both static (e.g., speed limits) or dynamically controlled via traffic controllers or traffic management centers (TMCs) (e.g., variable speed limits (VSLs)).

B. User Acceptance and Preferences

The user acceptance aspect is related to the trust, preferences, and comfort of the driver, passenger, owner, or fleet manager of automated vehicles. Passengers might be able to specify their preferences with respect to how they would like to be driven. Similar to conventional vehicles, which often offer different settings as sport driving or eco-driving, automated vehicles might have pre-set driving styles. Some features could be enabled or disabled based on preferences for safety, for efficient power usage, or for comfort. More advanced interfaces could allow the user to tweak or set parameter values in the ADS as they most see fit (e.g., time-headway, acceleration and speed settings). Users will be able take back control from the ADS if they so prefer, or override some driving automation systems, for example, by pressing the gas pedal to increase the speed or overtake.

This aspect also considers the level of acceptance and the interactions of other road users with automated vehicles. Human drivers might adapt their driving behavior or change their decisions for various maneuvers when they interact with an automated vehicle. Automated vehicles might be equipped with external human machine interfaces (eHMIs) which are relevant when discussing behavioral adaptation as they allow other road users (i.e., human drivers, cyclists, and pedestrians) to identify an automated vehicle.

C. Vehicle System

The vehicle system aspect considers the characteristics and technologies of the ADS and driving automation systems of the vehicle. Also the type of vehicle, the SAE level of automation, the physical appearance, the size, and the weight of the vehicle. The ODD specification of the vehicle is a key consideration of this aspect, which is defined by, among others, the sensor system, braking system, steering system, suspension system, tires, powertrain, and hardware and software of the driving automation systems.

D. Vehicle Sensor-Based Perception

Some the most commonly implemented sensors in automated vehicles are cameras, radar, lidar, and ultrasound. This aspect refers to the perception achieved by the sensors of the vehicle, or the object and event detection part of the OEDR done by different sensors, and not to the sensors themselves. The ADS of automated vehicles at SAE levels 3 to 5 should be able to perform all DDTs based entirely on the vehicle sensor-based perception and is therefore critical for automated driving.

The sensors track the relative position, the relative speed and motion of surrounding vehicles or objects, and also recognize what these objects are. Different sensors have different range of detection, achieve different levels of accuracy, and operate optimally under specific conditions. When conditions are not ideal (e.g., heavy rain, fog, occlusion), the detection and therefore the perception of the automated driving context might not be accurate. Additionally, OEMs that equip vehicles with the same set of sensors, may implement different software solutions for interpretation, resulting in different performance of the vehicle sensor-based perception.

E. Vehicle Connectivity

On board sensors provide information limited to line-of-sight surroundings and with limited range. Information received through wireless connectivity could provide information about the entire route and an extra layer of perception for all strategic, tactical and operational decisions.

Vehicles could communicate with other vehicles, with other road users, and with the infrastructure (vehicle-to-everything (V2X) communication). Depending on the information shared, different applications like cooperative driving, extended perception, and remote driving could be enabled. Vehicles could for example share information about their capabilities, their route, their intended maneuvers, or about their current perception. Vehicles could receive information about weather conditions, traffic states, emergency services, traffic signal states, incidents, speed limits, map information, etc.

The protocol on which this information is transferred (e.g., Wi-Fi, LTE, NR), might affect coverage, error rates, and latency. Depending on how the information is used, the error rates and latency could influence the operation of the vehicle.

F. Physical and Digital Infrastructure

The physical infrastructure considers the geometric design of the roads and the road environment (i.e., urban, rural, motorway). On motorways or major arterials with one directional traffic, with absence of pedestrians and with few traffic signals, vehicles deal mostly with keeping safe distances, staying within the lane, and eventual lane changes and merging. On urban roads, vehicles need to keep track of trees, parked vehicles, bicycles, pedestrians, etc. The state of the physical infrastructure (e.g., quality of lane markings, pavement quality, visibility of traffic signals and traffic signs), can also influence the operation of the vehicle.

The digital infrastructure considers the static and dynamic digital representation of the physical world with which the vehicle interacts. This includes high-definition maps, dynamic traffic information, advanced advice related to optimum routing, sensors in the infrastructure, etc. [25]. The digital infrastructure enables not only the transmission of detailed information to vehicles, but also the required sensoring and data collection of the information to be transmitted. Detailed 3D information of road geometry allows the vehicle to anticipate slopes and curves, plus HD maps and simultaneous localization and mapping (SLAM) help the vehicle keep track of its location. Furthermore, infrastructure at higher ISAD levels allow for enhanced perception, and more accurate information both static and dynamic, throughout the entire route.

IV. How Has Previous Work Considered the Aspects

In this section we present a literature review aimed to identify how the proposed aspects have been considered in studies that have presented microscopic traffic simulations of automated driving, as well as the effort from empirical studies and field tests that have focused on automated driving.

A main benefit of conducting empirical investigations and field tests is that they provide real data closest to the ground truth. However, empirical work and field tests require a lot of effort, resources, and often have a narrow scope. On the other hand, investigations based on traffic simulations are less expensive to conduct and provide large amounts of data. The downside is that results obtained from simulations are only as good as the mathematical models involved and as the assumptions made behind them. Strategies to deal with the attached uncertainties when modeling automated driving in traffic simulations have been proposed in Mintsis [26] and in Olstam *et al*. [27]. The proposed strategies are based on the limited available empirical data and/or on recommendations from OEMs. Therefore, investigations based on traffic simulations not only greatly benefit from but also require findings of empirical work.

The number of studies that have conducted field tests with automated vehicles are fewer in comparison to the studies that have used traffic simulations. Empirical work and field test studies found in the literature have often used controlled scenarios (i.e., a closed test track) to collect data, or took place at operation research testbeds which are limited in number around the world. If conducted in public roads, it has been under several restrictions to guarantee the safety of other road users. The findings of many empirical studies can directly be related to some of the proposed aspects. The studies have focused on the interactions between humans and automated vehicles, on the performance of driving automation systems in different environments, and on the implications of connectivity.

The main focus of microscopic traffic simulation studies found in the literature has been on assessing the effects caused by automated vehicles with respect to traffic safety, traffic efficiency and environmental impacts. The focus has mainly been on investigating light vehicles (i.e., cars) cruising on motorways and on urban roads. Some of the proposed aspects have been considered more thoroughly than others, either by including them in the model for automated driving, or in the experimental setup of the simulations.

In the following sub-sections we present aspect by aspect how each one has been commonly considered in studies that have used traffic simulations, as well as related findings from empirical studies.

A. Authorities

Investigations using traffic simulation of automated driving have seldomly explicitly mentioned the role of the authorities in their experiments. traffic management centers (TMCs) which play the role of the authorities, are often assumed to have detailed information about the state of the traffic, about vehicles, about maneuver intentions, positions, current speeds, desired routes, etc. Dynamic control strategies have been investigated using traffic simulations based on this more detailed information and beyond traditional traffic indicators. Grumert *et al*. [28] and Han and Ahn [29] presented traffic simulations on VSL systems including connected vehicles and the assumption made was that vehicles always comply with the VSL recommended speed. This was modeled by adjusting the desired speed parameter according to the dynamic strategy of the VSL during the simulation. Similarly, in Lee *et al*. [30] automated vehicles accommodate their driving to the level of aggressiveness allowed (or recommended) for automated driving by the authorities based on the observed state of the traffic. The change in aggressiveness is done by changing gap-related and acceleration parameters in the driving model, also during the simulation. Traffic simulations on signal control schemes at urban intersections [31] and on road hazard warning systems [32] included mixed traffic and implemented specific responses for automated vehicles during the simulations, such as change of speed, acceleration or deceleration, or lane changes. In Khattak *et al*. [33] a centralized cooperative driving strategy was investigated in which connected vehicles were diverted into specific lanes during the simulation based on the state of the traffic, again assuming full compliance.

The role of the authorities has also been considered in the experimental setup of the simulations and not just by making changes in the model for automated driving. In Ramezani [34] and in Ma and Wang [35], authorities define the areas where automated driving is permitted (i.e., geofencing), in this case automated vehicles were allowed only in specific lanes of the motorway.

In empirical studies there is seldomly consideration of the role of authorities. However, some have collected data from field tests about dynamic regulations. Their findings can be used to validate the findings from traffic simulation studies. In Zhao *et al*. [36] vehicles connected to signalized intersections in an arterial corridor receiving speed advise had a significant reduction in fuel consumption and emissions compared to non-connected vehicles. Qi *et al*. [37] conducted a field test in an interstate corridor in the U.S. to evaluate overall traffic conditions, safety and the operational impacts of a VSL system on both connected and non-connected vehicles, and found that the VSL system improved traffic operation even at a low penetration rate of connected vehicles.

Testing with automated vehicles on public roads, and especially when new technologies are involved, requires the admittance and approval of the relevant authorities. For example, the Netherlands Vehicle Authority - RDW [38] and the Swedish Transport Agency [39] have developed admittance procedures for practical tests for vehicles with new technologies and functionalities on public roads. The licensing authority may approve testing of automated vehicles on only specific types of roads, traffic conditions or weather conditions to guarantee the safety of all road users. In such cases the automated vehicles must adhere to the road regulations and the traffic rules.

B. User Acceptances and Preferences

The user acceptance or preferences is another aspect that is not often considered in investigations using microscopic traffic simulations including automated vehicles. A common implicit assumption is done by including scenarios with varying market penetration rates of automated vehicles in the experimental setup of the simulations [30] [40], [41], [42], [43]. An increasing market penetration rate implies that automated vehicles are adopted and accepted by other road users and the society.

Acknowledging that users can change settings on the driving automation systems of the vehicle is another way this aspect has been considered. In Kesting *et al*. [44] the model for the ACC controller used in traffic simulations differentiates between two parameters, a required acceleration and a comfortable acceleration. This comfort setting could be set by the passenger. Also dealing with passenger comfort, Nguyen *et al*. [45] used microscopic traffic simulations to investigate effects on travel delays for different passenger comfort requirements in an automated public transport system, by including changes in parameters on acceleration.

In traffic simulations that considered transitions of control from automated driving to human driving [26], [46], the transition is modeled by introducing a more erratic driving during a defined short period, representing a driver becoming aware of the situation until taking control of all driving tasks.

With respect to the transition of control, Varotto *et al*. [47] collected driver behavior data to analyze and quantify the magnitude and duration of adaptations in driving behavior characteristics (e.g., speed, acceleration, headway) during the transition of control from a full-range ACC system, finding significant changes in driver behavior characteristics and providing quantitative values. The frequency of transitions of control, the driving conditions that lead to these transitions of control, and the magnitude and duration of adaptations in speed, acceleration, distance headway and relative speed were investigated. When drivers deactivate the full-range ACC system the speed decreased significantly and it increased significantly after the system was overruled by pressing the gas pedal. Findings indicate that drivers prefer to resume to manual control at low speeds to avoid potentially safety-critical traffic situations [48], when approaching a slower leader [49], [50], and when changing lanes [51]. Drivers also tend to regulate the driving speed when changing lanes [52], [53]. Studies have also analyzed disengagement and accident reports of commercial automated vehicles [54], [55]. Dixit *et al*. [54] found the lack of trust to increase likelihood of the driver to take control of the vehicle. Increase in traveled miles was found to increase takeover reaction time suggesting increase in trust on the vehicle.

Empirical studies have also investigated the interaction of human drivers with automated vehicles. The trust on automated vehicles could affect these interactions [56], [57]. For example, Rahmati *et al*. [56] found that the car-following behavior significantly changes when following an automated vehicle. Human drivers felt more comfortable following the automated vehicle (i.e., drove closer to them and put less weight on the crash risk). Additionally, the investigation included a traffic simulation experiment with these findings which highlight the importance of including the human behavior adaptation when considering mixed traffic conditions. Zhao *et al*. [57] and Wu *et al*. [58] found that significant changes in driving behavior only occurred when automated vehicles were identifiable.

Other studies have investigated how the inclusion of external human machine interfaces (eHMIs) on automated vehicles affect the behavioral adaptation of other road users [59], [60], [61], [62]. They found that eHMIs can improve interactions with automated vehicles and that some aspects of the eHMI such as the color, the position on vehicle (e.g., bumper, roof, windshield), and the type of interface (e.g., text, image), can affect these interactions.

C. Vehicle System

The vehicle system aspect is perhaps the most explored aspect in traffic simulation studies. Even though the ADS refers to the hardware and software that are collectively capable of performing the entire DDTs on a sustained basis [19], the ADS has been widely reduced to an ACC system or a cooperative adaptive cruise control (CACC) system (i.e., ACC enhanced by vehicle-to-vehicle (V2V) communication). In traffic simulation studies the ACC or CACC is commonly considered as the main driving automation system. In Bose and Ioannou [63], the ACC was modeled by a throttle and brake controllers, while non-ACC vehicles were modeled using the Gipps car-following model [64]. The impact of CACC on the traffic flow was investigated in van Arem *et al*. [65] using a parametric model. In Kesting *et al*. [44] and Kesting [66] a traffic adaptive cruise control (TSA-ACC) was proposed and was modeled by changing the parameters on the ACC model during the simulations. In Xiao *et al*. [67] the CACC that provided driving automation included a collision warning system where a fallback to human driving would occur. Gáspár and Németh [68] considered an ACC controller that adapted to both the traffic state and the topographic information. An evaluation of different ACC systems using traffic simulations is presented in Goñi-Ros *et al*. [69]. In some traffic simulation studies, automated vehicles are explicitly differentiated between connected and non-connected automated vehicles [70], [71], [72], [73], [74]. However, often this differentiation only refers to either an ACC or CACC system.

Few of the aforementioned studies describe or mention the lateral motion control. Nonetheless, examples of studies investigating lateral motion control systems dealing with lane changing and merging maneuvers of automated vehicles are Luo *et al*. [75] and Sun *et al*. [76]. They rely on V2X communication for cooperative maneuvers, or on the assumption that other vehicles are implemented with the same lateral motion controllers. Often the lateral motion control models used for automated driving is the same used for human driven vehicles, a research gap highlighted in Do *et al*. [77] with respect to how to model automated driving in traffic simulations.

Another approach to describe and model the vehicle system in traffic simulations is based on the expected differences between automated driving and human driving. In Olstam *et al*. [27] conceptual descriptions of four different types of driving behavior for automated vehicles (Rail-safe, Cautious, Normal and All-knowing) were developed and implemented by adapting parameters in the

Wiedemann car-following model and lane changing models [78], based on field tests of vehicles with ACC and CACC and on general expectations. Some expectations are the capability of automated vehicles to perfectly handle the DDTs, the capability of shorter reaction times and always react in the same way to every event, showing little variations resulting into more deterministic models. Other examples in which automated driving was modeled by changing parameters in behavioral models for human driven vehicles include [40], [41], [79].

The vehicle system in terms of e.g. the heterogeneity in ADS logic has also been considered on the experimental setup of traffic simulations, by conducting experiments where automated vehicles all had the same ADS [80], [81], by considering more than a one ADS but only one at a time [40], or by considering mixes of different types of ADSs coexisting [12], [26], [27], [71].

In some to model the vehicle system has been proposed. In Hallerbach *et al*. [82] a hybrid simulation framework was proposed that incorporated vehicle dynamics simulation, traffic simulation and cooperation simulation to identify critical scenarios for automated vehicles. The vehicle dynamics simulation provided a digital prototype of the vehicle system including driving functions, sensor setup, etc. In Olstam and Elyasi-Pour [83] a model including truck vehicle dynamics and a fuel minimization ACC for trucks was coupled with Vissim [84] to study effects on traffic performance and energy efficiency for different penetration rates. In Mullakkal-Babu *et al*. [85] a lower operational layer with steering and acceleration control were integrated into a traffic simulation framework. Adding the nanoscopic or submicroscopic operational layer contributed to better simulating lateral maneuvers (e.g., curve negotiation, corrective steering, lane change abortion), and provided additional operational state variables (e.g., vehicle heading, wheel steering angle) compared to microscopic traffic simulations. There are also studies that tried to enhance vehicle longitudinal motion modeling, as the MFC model [86] or the model in Rakha *et al*. [87] which include simplified modeling of the powertrain integrated with power-based vehicle fuel consumption and emission models.

Empirical work found in the literature has conducted field tests focused mainly on evaluating the performance of ACC and CACC as driving automation systems. The study by Shladover *et al*. [88] was among the first field test studies which collected empirical data to the assess the impact of ACC and CACC on traffic performance. Relevant variables for defining the car-following control algorithms for ACC or CACC vehicles were identified and implemented in the AIMSUN [84] microscopic simulator. The identified variables were: speed of the vehicle, desired speed set by driver, speed limit of road, speed error, acceleration, spacing between vehicles, desired spacing, spacing error, and desired time gap. In Milanés and Shladover [89] data was collected also from vehicles with ACC and CACC to derive models useful for microscopic traffic simulations which included the delays associated with sensor signal processing or vehicles actuators. Shi and Li [90] conducted a field test with commercial ACC systems and tested different headway settings, estimated a car following model, and models for safety and string stability. Stern *et al*. [91] showed in a field experiment that a longitudinal controller can dampen the traffic instability and stop-and-go waves caused by human driving. In Makridis *et al*. [92], [93] the response time of the ACC controllers were quantified, the string stability investigated and doubts about the positive impacts of ACC systems on traffic flow efficiency were raised. Similarly, He *et al*. [94] and Ciuffo *et al*. [95] found that ACC systems will possible lead to higher energy consumptions, introduce safety risks, and lead to string instability.

Other empirical work has focused on investigating the effects of platoons which is an application of automated driving. Knoop *et al*. [96] conducted a field test with vehicles platooning and studied the string stability and fuel consumption. Tiernan *et al*. [97] tested vehicles platooning and proposed a control structure to suppress intra-platoon errors in position and speed, and increase platoon stability without compromising safety.

Recently, an open-access database (OpenACC) of different experiments with vehicles equipped with state-of-the-art commercial ACC systems has become available allowing to further investigate the effects and properties of ACC systems [98]. In Gunter *et al*. [99] vehicles with ACC systems from different OEMs were tested, in addition to investigating the string stability and disturbances, the data collected has also been made available. Other open datasets of commercial projects such as those by Waymo [100] and Lyft [101], [102] also provide valuable data that can be used to better model automated driving.

D. Vehicle Sensor-Based Perception

The sensor-based perception is commonly considered in microscopic traffic simulations through parameters on detection range of other vehicles and objects. In Kesting [66] the proposed ACC model considered radars with a range of detection of 200 m, limited to detect only one vehicle in front and track its speed every 0.1 seconds (10 Hz), the model assumes sensors with negligible detection errors. Rahmati *et al*. [56], Mahmassani [70], and Talebpour and Mahmassani [74] described sensor systems with a detection range of 90 m$\pm$2.5%, capable of tracking 64 objects every 50 ms (20 Hz) with a horizontal angle of view of 35 degrees, automated vehicles were described to have six of these radars, two facing the front, two facing the back, and one facing each side of vehicle, however, in the included simulations only one vehicle in front was detectable within the 90 m range and only vehicles in the immediate adjacent lanes. Beyond the detection range automated vehicles were forced to assume the existence of an obstacle, which forced them to limit their speed. The inclusion of $\pm$2.5% in the detection range considers some variability in the performance of the sensors, although perfect detection was still assumed. The detection range considered in Olia *et al*. [72] was set at 150 m after showing that if set below 100 m the decelerations required would be very high if obstacles are assumed beyond the detection range. In a similar way, Ye and Yamamoto [103] considered the detection range of the sensors at 120$\pm$2 m but enhanced the perception to

300 m by assuming V2V communication. Bahram *et al*. [80] included a four-lane motorway and limited the lateral detection of vehicles to the adjacent lane and indicated that conflicts may emerge if cutting in vehicles coming from the second lateral lane were not detected.

Knauss *et al*. [104] did an investigation collecting data from focus groups and interviews, as well as studying existing research publications to answer the question about the challenges to be addressed for testing automated vehicles. They found that the challenge related to sensors and sensor models (used to simulate sensors) is among the top major challenges. Berk *et al*. [105] states, however, that validating sensor perception reliability with standard empirical tests is very challenging and impractical due to the large required test efforts, and the need for ground truth references to identify potential errors. Nevertheless, some studies focused on investigating the reliability of sensor systems can be found in the literature. Wang and Li [106] analyzed data from California's Autonomous Vehicle Disengagement Report Database to establish a relationship between the cause of disengagements from ADSs and the number of sensors on the vehicle. Their findings indicated that to prevent disengagements, at least 5 radar sensors and 3 lidar sensors should be implemented while the number of cameras could be based on the preferences of OEMs. Similarly, Boggs *et al*. [107] utilized data from the California Department of Motor Vehicles (DMV) manufacturer-reported disengagement to relate an array of attributes (e.g., location, cause, ADS maturity) to disengagements from ADSs. Their results illustrated that perception discrepancies are not a significant cause for disengagements, in other words, the sensor systems are very reliable.

Some field tests that focused mainly on driving automation systems also contribute valuable insights to the sensor-based perception aspect. Milanés and Shladover [89] calibrated their proposed ACC model with data obtained from a radar to track the speed of the vehicle in front and Lidar to track the distance, and included the delays associated with the performance of these sensors in their model. The results of the study on a CACC system by Lu and Aakre [108], showed a reasonably robust and stable performance for constant speed and distance tracking. The error for speed tracking was within 0.1 m/s and 0.3 m for distance tracking. Cafiso and Pappalardo [109] conducted a field test to evaluate vision-based systems in detecting lane markings and found that lane keeping system (LKS) functioned in over 97% under optimal conditions. Similarly, Reddy *et al*. [110] evaluated the performance of detecting lane markings of a LKS under different visibility and speed conditions. Their findings showed that the best performance was achieved in dark, dry conditions without streetlights, while the lowest performance was during wet, dark conditions with streetlights.

E. Vehicle Connectivity

The terms 'connected' and 'non-connected' automated vehicles are commonly found in studies using traffic simulations [70], [73], [74]. The approach to include communication between vehicles (V2V) is different than the approach to include communication with the infrastructure (vehicle-to-infrastructure (V2I)).

Modeling of the communication (e.g., V2V, V2I) in traffic simulation have commonly been done either by changes in the parameters or driving behavior models or by coupling a traffic simulation model with a wireless network simulator [111], [112], [113]. An overview of simulators for vehicular ad-hoc networks (VANETs) is given in [111] and examples of simulation platforms that combines the wireless network and traffic simulators can be found in [112] and [113].

In Olia *et al*. [72] V2V communication was included in the automated driving model by allowing automated vehicles to keep shorter gaps and also allowing them to perform cooperative maneuvers for merging and for lane changes, improving road capacity. In the CACC model of Milanés and Shladover [89] vehicles keep shorter gaps between them since the information about the motion state of the leading vehicle is transmitted and not estimated, allowing for smoother reactions and solving string instability issues of ACC systems. In van Arem *et al*. [65] vehicles with CACC were also modeled by keeping shorter gaps between them, additionally they state that V2V should not be restricted to the longitudinal motion control. In Zhang and Orosz [114] the effects of various heterogeneous connectivity structures and information delays on the longitudinal dynamics of connected vehicle systems (CVSs) with mixed traffic of conventional vehicles and CACC vehicles were studied. They proposed a motif-based approach for modular and scalable design of CVS. They also tested the CACC mechanism and assessed the plant stability as well as head-to-tail string stability in selected conditions using numerical simulations.

The use of V2V communication for lateral motion control has been the focus on recent studies. Rios-Torres and Malikopoulos [115] included vehicles with V2V which could perceive other V2V-enabled vehicles and share information about their speed and position to calculate an optimal acceleration in a merging zone. Williams *et al*. [116] took the same V2V approach to overcome the line of sight limitation due to sensor ranges, and proposed a strategy for an anticipatory lane change maneuver. Luo *et al*. [75] and Sun *et al*. [76] also proposed cooperative lane change maneuver strategies on highways, based on V2V communications modeled by allowing vehicles to interact with vehicles located further downstream, the connectivity is explicitly described as without loss or delays.

In both Zhang *et al*. [117], [118], a hybrid approach using MATLAB, Simulink and SimEvents [84] to include V2I communication is proposed, automated vehicles receive traffic control information with an included communication delay. Similarly, in Li and Wagner [119], a hybrid simulation approach is proposed for dynamic control strategies where SUMO and MATLAB [84] are coupled to include V2I communication, and used this approach to evaluate a VSL system. In Wang [120] the V2I communication is included by changing parameters on the ACC controller during the simulation based on the traffic state, while in McConky and Rungta [121] automated vehicles change their speed parameters based on the state of the traffic signal. In Talebpour and Mahmassani [74] automated vehicles update their desired speed during the simulation which is provided from a TMC.

In Talebpour *et al*. [73] a hybrid simulation framework to include the flow of information of V2V and V2I communications is proposed, they concluded that signal interference reduces the efficiency of the communications, and with that, also the performance of control strategies. This issue was also brought up in Mahmassani [70], and mentioned that studies investigating the flow of information unfortunately have focused more on the network topology and not on the effect of connected environments on traffic operations.

Regarding empirical studies, Ge *et al*. [122] proposed a longitudinal controller design for connected automated vehicles and experimentally evaluated the performance of their proposed connected cruise controllers utilizing beyond-line-of-sight information via V2X on real vehicles (two human-driven vehicles and one connected automated vehicle) under several driving scenarios and different communication network topologies. Their results demonstrated that a connected automated vehicle is able to avoid a severe braking maneuver and mitigate the cascade of braking events propagating from vehicles downstream by using V2X communication to get motion information of multiple vehicles ahead. Avedisov *et al*. [123] studied the effects of V2V connectivity on freeway traffic patterns, and adopted the empirical data fitted models from their test to study traffic dynamics with partial penetration of connected automated vehicles in a 100-car network by simulation. Their results indicate the long-range feedback can benefit the freeway traffic flow, and increasing the penetration of connected human-driven vehicles would enable the connected automated vehicles (even at a low penetration) to significantly improve the traffic efficiency.

A recent study by Ma *et al*. [14] conducted a field tests to investigate the impact of a connected environment on traffic performance. An integrated set of CACC platooning, cooperative merge, and speed harmonization applications were implemented in a fleet of five vehicles. The results of this study showed an improved traffic flow string stability. It was also found that the observed traffic performance was quite different from the expectations based on traffic simulations. The authors explain this difference due to additional factors that may impact the platoon performance, such as road geometry and communication quality.

Other empirical work has focused on investigating the effects of a connected environment on human driving behavior. Farah *et al*. [124] used empirical data collected from a field test to evaluate the impact on car-following behavior caused by a dedicated short range communication (DSRC)-based V2I co-operative system for intelligent road safety (COOPERS). The authors found that the system harmonized the behavior of drivers, reduced reaction times and also the range of acceleration and deceleration differences among them. Additionally, they found that V2I safety messages affected significantly the lane-changing and car-following behavior and calibrated the car-following model when using the system and compared it to the baseline scenario when not using the system. These calibrated models were later implemented in the microscopic traffic simulation tool PTV VISSIM [84] to assess the impact on traffic performance [125]. Farah and Koutsopoulos [126] also found that V2I warning systems were generally acceptable and useful from a driving safety aspect. Qiao *et al*. [127] used a RFID-based V2I to warn drivers approaching work-zones and observed that drivers took earlier action to reduce speeds. Yu *et al*. [128] found that when drivers receive speed recommendations through a DSRC-based V2I when approaching a signalized intersection, their reactions could be predicted with high accuracy at a distance of over 80 m away from the intersection, and also that the majority of drivers complied with the speed recommendations. These results indicate that V2I significantly affects driver behavior and as a result traffic flow efficiency and safety.

F. Physical and Digital Infrastructure

The physical infrastructure is commonly considered in the simulation setup of traffic simulations in terms of which type of roads environments are investigated. The type of road is not exclusive to the research of automated driving and depends on the purpose of each investigation. However, traffic simulations on motorway environments including automated vehicles is more common than urban environments. Few microscopic traffic simulation tools have the capability to assess the impact of the physical infrastructure on the longitudinal and lateral behavior of vehicles. Some examples are traffic simulation tools for rural roads (e.g., RuTSim [129], [130], TWOPAS [131]), in which speed adaptation to the road geometry is generally more important than for urban roads. An exception for urban roads is Kharrazi *et al*. [132] which presented a speed adaptation model (implemented in SUMO [84]) that consider curvature based on GPS-data.

Many traffic simulations focusing on traffic control strategies explicitly state as assisted by the digital infrastructure [30] [33], [120], with different ISAD levels of digitalization assumed. In Khattak *et al*. [33] a cooperative lane control application for automated vehicles considered a digital infrastructure at ISAD level A. The assistance provided by the infrastructure was implemented in the microscopic traffic simulator PTV VISSIM [84] by replacing the driver behavior with a dynamic link library (DLL) that included the algorithm for lane control and a CACC logic. In [120], a digital infrastructure at ISAD level B is considered, the role of the infrastructure was captured in the simulation by changes in gap-related parameters during the simulation. In traffic simulations that aren’t explicit about the role of the infrastructure, a digital infrastructure ISAD level D can be considered as the most common assumption, which provide digital maps and static regulatory information to assist automated vehicles.

Research based on empirical data has studied the impact of the physical infrastructure on the performance of different driving automation systems. García *et al*. [133] found that the horizontal curvature of roads limited the maximum speed that vehicles could attain without disengaging the ADS. Reddy *et al*. [110] and García and Camacho-Torregrosa [134] found that the lane width affected the ability of LKSs to detect the lane markings, 2.5 m was the maximum width which always required the intervention of the driver.

Empirical work that considered the role of digital infrastructure has investigated the effects on human driving behavior when receiving messages from the infrastructure through road-side units (RSUs). These studies have been presented in the previous subsection under the connectivity aspect since V2I communication relates directly with the digital infrastructure [124], [125], [126], [127], [128].

V. Discussion

In this section we present the main findings with respect to each of the proposed aspects. In addition, we discuss the implications and limitations of the common approaches taken in microscopic traffic simulation studies, and motivate the need for more empirical work and field tests. Specific research needs regarding each aspect were identified and are proposed. Each of the proposed aspects has been explored to a different extent in the literature, and it is challenging to extract the assumptions and conditions considered regarding each one of them because they have mostly been considered indirectly.

Road **authorities** at the national level encourage research on the implications of automated driving on traffic safety and efficiency and the infrastructural adaptations needed for its deployment on public roads. However, in order to collect data from field tests and given the existing uncertainties with respect to the safety implications, the public acceptance, and the performance of the automated driving system (ADS); road authorities currently provide guidelines to safely test and operate automated vehicles on public roads. Their main concerns relate to changes in liability and to the regulation of automated driving. The focus of studies that considered the role of road authorities has been mostly on dynamic regulation strategies (e.g., variable speed limit (VSL) systems, geofencing), and their implications on traffic flow. Most, if not all, traffic simulation studies of automated driving assume full compliance with present traffic rules and regulations. Authority decisions on e.g., liability requirements regarding the compliance of automated vehicles to both static and dynamic road regulations as well as privacy concerns regarding the sharing of information between vehicles influence how automated driving is operated. Hence, future studies using traffic simulations need to consider decisions already taken by the authorities or consider the potential uncertainty with respect to such decisions. Results of these simulations can then inform road authorities under which conditions automated driving can be admitted on public roads without compromising traffic safety and efficiency.

The **user acceptance and preferences** could determine how the ADS handles the dynamic driving tasks (DDTs). Although at lower SAE levels of automation the driver is responsible for the DDT fallback, the driver could take over control of all or some of the DDTs if they so prefer regardless of the SAE level of automation. Empirical studies on transitions of control have largely focused on drivers taking over the longitudinal motion control from an ACC system, and some have even proposed mathematical models to be implemented in traffic simulations. Unfortunately, most traffic simulation studies have not considered this, instead of including the interaction between the driver and the ADS during the transitions, there has been a 'jump' between automated and human driving. Transition of control can have significant impacts on traffic flow efficiency and safety. Thus, it is crucial to incorporate them in traffic simulations and further research is needed on how to model and implement transitions of control in traffic simulation models and their implications on traffic safety and efficiency. This is of particular interest when considering vehicles at lower SAE levels of automation with a restricted operational design domain (ODD), mixed traffic conditions, and in geofenced environments where automated driving is restricted to defined areas and an eventual transition of control is mandatory. There is however, still need for empirical studies and research focusing on transitions of control from lateral motion control systems (e.g., LKS).

The willingness to use automated vehicles and the adaptation of other road users to the presence of automated vehicles are additional dimensions of **user acceptance and preferences**. Microscopic traffic simulation studies have considered varying market penetration rates of automated vehicles in their experiments, but market penetration rates do not necessarily capture the actual use of ADSs. Socio-economic characteristics and driving preferences of users have been found to play a significant role in the attitude towards automated driving. Moreover, both lateral and longitudinal control systems could allow for users to choose or define parameters for a safer or a more comfortable operation, and if so, data regarding preferred settings should also be collected. Disengagements by drivers were found to be affected by their trust in the vehicle, which seemed to increase with the distances driven. Additionally, traffic simulation studies of automated driving in mixed traffic have largely overlooked the possibility that other road users might adapt their behavior due to the presence of automated vehicles. This behavioral adaptation is likely to be different depending on the penetration level. external human machine interfaces (eHMIs) of automated vehicles also play a role in the behavioral adaptation of other road users and could also be accounted for in microscopic traffic simulations. Future research, therefore, could take several directions. It could study the preferences of drivers with respect to the longitudinal and lateral driving parameter settings such as time gap and speed in different driving contexts. Moreover, the driving behavior of human-driven vehicles in the presence of automated vehicles is vastly unexplored. Research on this could investigate the effect of factors such as recognizability and different automated driving styles. Incorporation of the effects of eHMIs in this respect, particularly in traffic simulation, also has many research possibilities.

The characterization of the **vehicle system** done in traffic simulation studies by using an ACC/CACC model has been a helpful simplification of ADSs to investigate effects caused by longitudinal dynamics of automated vehicles. Empirical works have provided valuable insights for developing, calibrating, validating and improving ACC models. However, ACC systems deal only with the longitudinal motion control, the lateral motion control of automated vehicles has not been considered as much and often is not even mentioned. Hence, a more elaborate approach to characterize the vehicle system is required, which should include other driving automation systems, the logical hierarchy and the dependencies between them. There is only very limited publicly available data from OEMs. Thus, field studies should focus on collecting data about the performance of ADS beyond the longitudinal motion control. The performance could vary depending on the conditions of testing and also between different OEMs even at the same SAE level of automation and ODD. This data would allow to better capture the variability between different ADSs, and to avoid that all automated vehicles in traffic simulations show the same response under a given situation. Traffic simulation experiments including automated driving need, to a larger extent than today, to capture the heterogeneity in ADS and their driving behavior since the heterogeneity influences many traffic phenomena (e.g., traffic stability and hysteresis). Lastly, both traffic simulation studies and empirical works on automated driving should include a more detailed description of the ODD considered in their investigations. The vehicle system has a specific ODD and findings should be framed within the considered ODD elements.

The **vehicle sensor-based perception** is a safety-critical aspect of automated driving. In the absence of external aides for perception, it is critical for both the object and event detection and response (OEDR) and for the correct operation of longitudinal and lateral motion control systems. Nevertheless, this aspect has not been explored in-depth in neither microscopic traffic simulation-based studies nor in empirical works. With the burgeoning technical advancements on sensor systems, investigations about sensor-based perception become even more complex. Microscopic traffic simulation models used for both human and automated driving include parameters on the detection range of other vehicles and objects, and a perfect perception is in principle always assumed. The difference has been on the parameter values used. The assumption of perfect perception is questionable. There has been some empirical work on the performance of some driving automation systems (e.g., ACC, LKS), which utilize different sensors to function. However, it can be dangerous to investigate sensor perception reliability in real life, and thus it is not always practical to validate findings with standard field tests. With the advancement of ADS simulation platforms (e.g., CARLA, SVL Simulator, Voyage DeepDrive), detailed simulation of sensors including combination of sensor suites and sensor errors, can be implemented at a nanoscopic level. Such simulations platforms can provide valuable insights for the development of perception models that can be included in microscopic traffic simulations. It is even possible to implement these nanoscopic simulation platforms into microscopic traffic simulation tools, but at high computational cost and restricted to scenarios with a limited number of vehicles. Additionally, the sensor-based perception does not only depend on the reliability and specifications of the different sensors but also on the algorithms and computational capabilities of the computers on board. Therefore, it is also important to investigate and quantify the possible sources of delay in the interpretation of the automated driving context.

The **vehicle connectivity** is considered in traffic simulation by including changes in the models for automated driving and/or by running the simulation in combination with a wireless network simulator. Changes in the models for automated driving aim to portray the expected differences between connected and non-connected automated vehicles, and to assess implications of specific V2V applications (e.g. platooning, cooperative driving). Wireless networks simulators are used to portray V2I communication and to assess more centralized applications (e.g., VSL systems). The common assumptions are a 100% communication success rate and zero latency, both which are far from being accurate. Therefore, effects of communication failure or compromised connectivity should be further investigated in future research. Details are not yet clear about the range in which vehicles can communicate nor about the information that vehicles will exchange (with respect to e.g., privacy and proprietary issues). More empirical studies are required on vehicle connectivity performance with focus on coverage, latency, range, and reliability, as well as on automated driving applications enabled by vehicle connectivity. Some effort on this has come from the telecommunications industry, but not under real traffic conditions with high density of vehicles. Therefore, future traffic simulation models should incorporate findings from empirical studies on vehicle connectivity performance and/or endogenous models for vehicle connectivity.

The **physical infrastructure** in traffic simulation studies has been mostly differentiated between urban roads (e.g., intersections) and motorways with limited considerations on effects of geometric road design. There is a need for further research to also include the implications of the geometric road design (e.g., lane width, road curvature, vertical slopes), as well as infrastructure quality (e.g., road surface condition, lane markings) in traffic simulation models. These details become important when describing ODD considered in the investigations. Speed adaptation, acceleration and deceleration when approaching curves can have an effect on the overall traffic flow. Recent empirical studies have demonstrated the effect of some aspects of the physical infrastructure on the operation and performance of automated vehicles. The performance depends on the specification of the ADS and on different OEMs. Field tests with systems from different OEMs are needed to reach comprehensive conclusions. Future empirical studies should focus on identifying edge cases stemming from the infrastructure side which are vital for the safe operation of automated vehicles.

The **digital infrastructure** has been considered in traffic simulation studies that focus on assessing dynamic traffic regulations or in cases in which the infrastructure provides some level of support (e.g., cooperative maneuvers, enhanced vehicle perception). This has been done by changing parameters related to the perception, or by dynamically changing driving parameters during the simulation depending on the state of the traffic. There are some limitations in these approaches. How the digital infrastructure estimates the state of the traffic in reality, and the expected accuracy of this estimation is not considered. The nature of the messages transmitted from the digital infrastructure (e.g., mandatory or advisory) is not differentiated and automated vehicles are assumed to always comply with them. A recommended practice for traffic simulations is to explicitly state the assumptions made with respect to the digital infrastructure, and also include how these assumptions affect automated driving. A suggestion is to at least state the level of infrastructure support for automated driving (ISAD) considered. Edge cases (e.g., poor visibility conditions, deteriorated quality of road infrastructure elements) could also be examined as the digital infrastructure could aid the perception outside immediate field of view. In some field tests the effect of safety messages and speed advisories from V2I systems on human drivers was investigated and found that they significantly affect the observed lane-changing and car-following behaviors. In a similar way, how ADSs would respond to such messages in respect to the lateral and longitudinal motion control, and processing delays could be investigated in future field tests.

The situational awareness of human drivers and the perception and interpretation of the **automated driving context** by automated vehicles, is commonly simplified and modeled at very low level of detail in microscopic traffic simulations. Vehicles are assumed to perfectly perceive all relevant information (e.g., relative position, relative speed) about surrounding vehicles and objects, and about the infrastructure. This assumption is not realistic even under optimal conditions. Errors in perception are rarely considered even though methods to model human errors in estimating distances and speeds of other vehicles do exist. Models for automated driving should include performance deficiencies in the perception and interpretation of the automated driving context. Such approach should consider the expected performance of sensors, of connectivity, and the level of support from the digital infrastructure; with focus on quality, range, latency, and processing delays for both interpretation and response.

The deployment of automated vehicles will have many different implications. Traffic safety, traffic efficiency, traffic control strategies, environmental impacts are some examples of the areas being investigated. The proposed aspects will be of different relevance depending on the end goal of each area of research. User preferences on how the ADS should operate have a big impact on traffic safety and traffic flow efficiency. The vehicle system and the physical infrastructure are perhaps more relevant to environmental concerns. Connectivity and the support from the digital infrastructure could enable applications that could improve safety for other road users, and enable new applications for traffic control strategies. Examples are vast, and considering some of the aspects as more relevant depending on the application is expected. Nevertheless, we can conclude from this discussion section, that all aspects will influence the operation of automated vehicles, and should be considered at some level regardless of the area of research.

Calibration studies of traffic simulation models including automated driving are few since real world data on automated driving is limited and/or proprietary data. Hence, when more data on automated driving becomes freely available, future research should focus more on calibration and validation and less on model development.

Finally, since the assessment of automated vehicles' benefits and drawbacks are inferred based on the relative comparison with simulation results for human driving, this calls for improving current microscopic traffic simulations that are mostly collision-free, and incorporate a more realistic and accurate modeling of human behavior. Furthermore, it is important that traffic simulation of mixed traffic capture the essential differences in e.g. perception and behaviour between human and automated driving in a consistent way.

Various microscopic traffic simulation software have different capabilities and limitations with respect parameters' adaptation of the inbuilt models versus interfacing of external models [13], [135]. Therefore, a meta-analysis of the results from these different microscopic traffic simulation software is recommended for future research.

VI. Conclusion

The level of coverage found in the literature with respect to each aspect differs greatly. Empirical studies have put more effort on investigating user preferences around specific driving automation systems (e.g., ACC) of the vehicle system. The observed performance of the sensor-based perception, the impacts of sharing of information through vehicle connectivity, and the impact of either the physical and digital infrastructure on automated driving performance have not been the general focus of empirical studies. Microscopic traffic simulation studies have mostly been based on assumptions to model automated driving, and as discussed in section IV, with limited use of insights from field tests or empirical findings. The focus has mostly been on the expected driving performance of the ADS of the vehicle system, and on the effects under different road environments (physical infrastructure). The inclusion of digital infrastructure to enable dynamic traffic control strategies and to improve traffic flow dynamics has also been focused to some extent. More attention is needed in investigating the role of authorities, the user preferences and include models consistent for the vehicle sensor-based perception and the performance of vehicle connectivity which not as explored using traffic simulations.

We have motivated and discussed why each aspect could determine how automated vehicles operate, and therefore, why considerations regarding each aspect need to be taken into account in models for automated driving in microscopic traffic simulations. The inclusion of mixed traffic, varying penetration rates, user preferences, transitions of control, heterogeneity of ADSs at different SAE levels of automation, description of considered ODD, and assumptions with respect to the behavioral adaptation of other road users; should be included in microscopic traffic simulation-based investigations in order to have scenarios that may soon become a reality and for the sake of scientific sound comparison between investigations.

The following is a summary of the research needs identified to develop and implement more accurate and realistic models for automated driving in microscopic traffic simulations. Data about the preferences of use of different driving automation systems (e.g., preferred safety settings, comfort settings, willingness to use) under different driving conditions is needed in order to forecast the heterogeneity of ADSs. The expected behavioral adaptation of other road users to the presence of automated vehicles, and the use of external human machine interface (eHMI) should be further investigated to be included in traffic simulations of mixed traffic. Empirical work on transitions of control from lateral motion control systems will extend and enhance the current proposed models for transitions of control. Field observations on maneuvers apart from car-following behavior will help develop, calibrate and validate models beyond car-following. Evaluations of the performance and identification of edge cases (with respect to e.g., road conditions, weather conditions, time of the day) of different driving automation systems from different OEMs, with particular focus on the performance of different types of sensors which are critical for the safe operation of the ADS, will help include variations on the models for automated driving and determine specific ODD requirements. Hybrid simulation approaches, which propose the use of different simulators (e.g., nanoscopic platforms, vehicle simulators, wireless network simulators) in combination with traffic simulators, will be useful as tools to gather synthetic data that otherwise might be too costly or unsafe to obtain. Lastly, inclusion of the expected performance of connectivity features and of sensor systems (i.e., range, latency, quality) as well as the implications of the physical infrastructure (i.e., road geometry design) on the perception models for automated driving is essential in order to capture key differences with human perception in microscopic traffic simulations. Future work focusing on these research needs will help to develop, enhance, calibrate and validate models for automated driving.

Modeling automated driving in microscopic traffic simulations involves different aspects as explained in this paper. Different stakeholders (e.g., authorities, transportation planners, OEMs, environmental agencies) may have a greater interest in one or a few of these aspects, depending on their study objectives. This could cause a high level of attention to be paid to those specific aspects while the intricacies involved with the other aspects may be partly or completely ignored. It is important for stakeholders to be aware of the existence of the other aspects and the nature of the roles they play. Such an understanding is possible with cross-domain knowledge exchange and through close collaborations between the stakeholders. The aspects proposed in this article i.e., the role of authorities, the user preferences, the vehicle system, the vehicle sensor-based perception, the vehicle connectivity features, the physical and digital infrastructure should help carry out investigations with a broader perspective and also should help to identify areas that might be easier to develop or implement, and which would bring greater benefits. Moreover, they will improve the use of microscopic traffic simulation as a tool to assess the traffic implications of automated driving.

Finally, this paper discussed the effect of each of the proposed aspects on the operational and safety constraints ignoring the possible interdependencies and overlaps between them. Such interdependencies, for example between user preference and vehicle system or between authorities and physical and digital infrastructure, do exist and should be further investigated in future studies.

Author Statement on Contribution

Haneen Farah: conceptualization, supervision, writing (original draft, and review and editing), and funding acquisition; Ivan Postigo: conceptualization, resources, writing (original draft, and review and editing), and visualization; Nagarjun Reddy and Yongqi Dong: conceptualization, resources, and writing (original draft, and review and editing); Clas Rydergren: supervision, and writing (review and editing); Narayana Raju: resources, and writing (original draft, and review and editing); and Johan Olstam: conceptualization, supervision, project administration, and writing (original draft, and review and editing).

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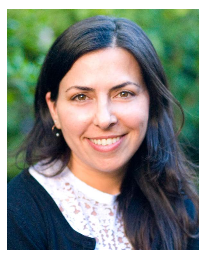

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