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Research Article

An Approach for Handling Uncertainties Related to Behaviour and Vehicle Mixes in Traffic Simulation Experiments with Automated Vehicles

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The introduction of automated vehicles is expected to affect traffic performance. Microscopic traffic simulation offers good possibilities to investigate the potential effects of the introduction of automated vehicles. However, current microscopic traffic simulation models are designed for modelling human-driven vehicles. Thus, modelling the behaviour of automated vehicles requires further development. There are several possible ways to extend the models, but independent of approach a large problem is that the information available on how automated vehicles will behave is limited to today's partly automated vehicles. How future generations of automated vehicles will behave will be unknown for some time. There are also large uncertainties related to what automation functions are technically feasible, allowed, and actually activated by the users, for different road environments and at different stages of the transition from 0 to 100% of automated vehicles. This article presents an approach for handling several of these uncertainties by introducing conceptual descriptions of four different types of driving behaviour of automated vehicles (Rail-safe, Cautious, Normal, and All-knowing) and presents how these driving logics can be implemented in a commonly used traffic simulation program. The driving logics are also linked to assumptions on which logic that could operate in which environment at which part of the transition period. Simulation results for four different types of road facilities are also presented to illustrate potential effects on traffic performance of the driving logics. The simulation results show large variations in throughput, from large decreases to large increases, depending on driving logic and penetration rate.

1. Introduction

The introduction of automated vehicles (AVs) is expected to affect traffic performance. Both urban and national road authorities are interested in how the introduction should be handled and what measures they should or should not apply to avoid negative effects and boost positive effects of the introduction of AVs. Investigations on how road design and traffic control measures affect traffic performance are commonly based on results from traffic models.

Microscopic traffic simulation models are state-of-the-art tools in transport planning. By simulating the movements of every vehicle, the models provide indicators (travel time, queue length, vehicle throughput, etc.) describing the performance of road facilities. Traffic simulation models are typically applied for designing, testing, and analysing road network sections with their traffic control facilities. They extend traditional highway capacity manuals (HCM) by providing methods for capacity analysis with varying demand, demand-actuated traffic control facilities, and coordinated signal control. Current microscopic traffic simulation models are designed for modelling vehicles with no automation. Hence, modelling the behaviour of AVs requires model extensions. These extended models also need to be calibrated and validated which is a problem since the systems to a large extent do not exist yet.

There are several possible approaches to incorporate the driving behaviour of AVs into traffic simulation models. However, there is limited information available on how AVs will behave. The information available so far is from tests with today's partly automated vehicles, mainly from test tracks. How future generations of AVs will behave will be unknown for some time. Thus, investigations of future traffic conditions with future versions of AVs and with higher penetration rates of AVs in general require consistent assumptions on how the behaviour of AVs will evolve.

Traffic simulation investigations of AVs commonly assume one type of automated vehicle and that all AVs behave the same. Furthermore, several traffic simulation investigations of AVs investigate vehicles with only one automation function, such as adaptive cruise control (ACC) or connected/cooperative adaptive cruise control (CACC). Investigations of one automation function at the time give valuable insights but limited knowledge on how the introduction of automated vehicles might affect the traffic system during the transition period. As discussed in Calvert et al. [1], the transition period from no to 100% AVs will most probably be long and it will likely include mixes of conventional (human-driven) vehicles and AVs with different levels of automation and different generations of automation functions.

Traffic simulation investigation of automated vehicles for estimation of effects during the transition period needs to apply a structured and systematic approach for handling the uncertainties related to how different generations of automated vehicles will behave and which mixes of different generations of automated vehicles that are likely to coexist at different stages of the transition period. The aim of this article is to present an approach for handling uncertainties related to the behaviour and composition of vehicle fleets with varying levels of automation in traffic simulation experiments for the transition period from mainly human-driven vehicles to 100% fully automated vehicles. This aim is approached by considering a discrete number of moments during the transition period, in addition to the commonly studied case of full automation and no automation.

This article is structured as follows. Section 2 gives an overview of traffic simulation models with respect to how the automated vehicles are modelled and how the transition period is handled in previous studies. The approach we suggest for the handling of different types of automated vehicles with different driving logics is presented in Section 3. Section 4 presents how these driving logics can be implemented in a microscopic traffic simulation model and Section 5 presents an example on how these driving logics affect traffic performance for four common road facility types. Section 6 ends the article with conclusions and needs for future research.

2. Approaches for Traffic Simulation including Automated Vehicles

Simulation of a traffic system that includes automated vehicles obviously requires modelling of the driving behaviour of the automated vehicles. There are several approaches for how the driving logics of automated vehicles can be incorporated in traffic simulation models (see Section 2.1). Furthermore, the transition from today's traffic situation with only a small fraction of partially automated vehicles to a future situation with a fleet consisting of exclusively fully automated vehicles will imply an extended time period with a range of mixes of vehicles with different levels of automation. Hence, traffic simulation experiments of the transition period need to consider a range of different automated vehicle behaviours. An overview of approaches for how the transition period has been handled in previously conducted simulation experiments is presented in Section 2.2.

2.1. Approaches for Modelling of the Driving Behaviour of Automated Vehicles. To the best of our knowledge, three approaches for how to include behaviour of driver assistance systems and automated vehicle functions are reported in the literature:

(i) Simulation of automated driving behaviour by adjustment of behavioural model parameters in the traffic simulation model

(ii) Replacement of behavioural models in the traffic simulation model with automated vehicle driving behaviour models

(iii) Extension of the driving behavioural models with "nanoscopic" modelling of automated vehicles, including simulation of sensors, vehicle dynamics, and driving behaviours

One of the simplest and most frequently used methods to include automated vehicles in traffic simulation models is to adjust parameters in an existing behaviour model for conventional vehicles to represent the driving behaviour of automated vehicles. This can, for example, be adjusting reaction time, gap-related parameters, acceleration parameters, and speed limit acceptance. There are traffic simulation investigations [2–13] that utilize this approach to simulate ACC/CACC equipped vehicles, or vehicles assumed to be highly automated in a specific road environment. Some investigations focus on one-lane roads without on/off-ramps and without overtaking possibilities (e.g., [14]), which, due to the fact that there is no lane-changing, is equivalent to simulation of just the ACC part of the automated vehicle functionality. The drawback of this approach is that the behavioural models in the traffic simulation model were developed to mimic human driver behaviour and it is unclear whether the driving behaviours of automated vehicles can be modelled by only adapting the parameters or if fundamental changes of the driving models are required. The advantage is that the unknown AV behaviour easily can be specified in terms of changes in relation to human driver behaviour, e.g., shorter reaction times and changed desired speed distribution.

The second approach is to develop new submodels for the driving behaviour of the automated vehicles [15]. The most common approach is to replace the car-following model used for simulation of conventional vehicles with a new model describing the longitudinal control by some ACC or CACC logic, while the existing car-following model is still used for simulation of the conventional vehicles in the mixed flow.

The third approach extends the common vehicle-driver unit approach used in most microscopic traffic simulation models to a "nanoscopic" approach. Here, nanoscopic refers to more detailed modelling of the vehicle, which may include modelling of sensors, engine, gearbox, and vehicle dynamics. This approach can, for example, be used to analyse the dynamic characteristics and control algorithms of vehicles (see, e.g., Bahram et al. [15]). The practical solution for these kinds of simulations is commonly some kind of cosimulation in which an AV or AV vehicle simulation model is connected to a traffic simulation model using an application program interface. This approach has, for example, been used by automotive industry researches to support the vehicle simulation with a more realistic description of the traffic surroundings (see, e.g., Tapani et al. [6]). Other examples where traffic simulation has been combined with more detailed simulation models of vehicle dynamics, engine, and support systems, are in [16–19].

2.2. Approaches for Simulation of a Mix of Automated and Manual Driven Vehicles. Even though simulation investigations of platoons of ACC or CACC are relevant and provide important insights on platoon stability (see, e.g., Bose and Ioannou [20], Milanés and Shladover [21], or Xiao et al. [22]), these investigations give limited knowledge on how the introduction of automated vehicles might affect the traffic system during the transition period and for common road facilities.

Several studies aim to investigate how AVs affect traffic performance, but in principle the analysis is limited to how the longitudinal control (e.g., ACC or CACC) affects the traffic performance (see, e.g., Bierstedt et al. [4] and Van Arem et al. [23]). In some cases, also the speed limit acceptance is considered, as in Calvert et al. [1]. In addition to these AV/ACC investigations, there are several simulation investigations focusing purely on the effects of ACC [9, 21, 24–31], as well as investigations on effects of some kind of CACC [11, 16, 21, 32–34].

It is rather common that traffic simulation investigations of AVs focus on simulations of separate AV functions such as ACC, CACC, and lane keeping assistant (LKA). However, since AVs will be more than a vehicle with an ACC, several investigations focus on traffic effects of AVs with different assumptions of speed limit acceptance and gap acceptance in addition to the longitudinal control. Calvert et al. [1], for example, conduct simulations of vehicles with ACC and LKA, while Aria et al. [2] and Atkins [3] make adjustments to the car-following and lane-changing-related parameters in Vissim to reflect expected AV behaviour based on statements in the literature. Another example is Olia et al. [33] which includes modelling of both AVs and cooperative AVs by extending a car-following model, with detection range and desired spacing, and by introducing a cooperative merging model.

In addition to modelling of the driving behaviours of AVs, it may for some applications also be important to consider differences in perception between conventional vehicles and AVs. As mentioned in Section 2.1, nanoscopic modelling or cosimulation of vehicle and AV technology and traffic simulation are two ways to include sensor capabilities and the vehicles perception of the surroundings. However, it is also possible to capture some parts of the potential differences in perception by adjusting parameters, such as look-ahead distance and number of vehicles considered in car-following or lane-changing. Such approaches for taking the sensor range into account are, for example, used in Talebpour and Mahmassani [16], Aria et al. [2], and Atkins [3].

There are few investigations that address the issue that different types of automated vehicles will exist and that the capabilities of the AVs and their driving behaviour will evolve during the transition period. Calvert et al. [1] present estimations of how penetration rates of ACC, LKA, high automation, full automation, and vehicle cooperation might evolve during the transition period. The estimations are based on a wide range of various predictions from industry, academia, and authorities. The estimations are used to illustrate that the transition period will be quite long and include a mix of different types of automated vehicles. However, it does not seem like the simulations conducted and presented in Calvert et al. [1] investigate scenarios with different mixes of automated vehicles but only investigate different penetration levels of ACC + LKA equipped vehicles. Instead, the variation in AV behaviour is modelled by the distribution of the model parameters of the AVs, assuming the same distribution in parameters independently of the penetration rate. Variations in AV behaviour are also addressed in Atkins [3], which considers nine different AV capability levels ranging from cautious to assertive. However, no mix of capabilities is considered in the conducted simulation experiments. The experiments are investigating the traffic effects of penetration levels between 0 and 100% for each capability level separately. In the Analysis/Modelling/Simulation (AMS) Framework for Connected and Automated Vehicle Systems in the USA [35], the plan is to use four vehicle categories: manual nonconnected, manual connected, automated nonconnected, and automated connected. Similar simulation experimental designs of mixed traffic consisting of manual human-driven vehicles, automated nonconnected, and automated connected vehicles are presented in Mahmassani [36] and Mattas et al. [37]. However, both the planned investigations in Mahmassani et al. [35] and simulations presented in Mahmassani [36] and Mattas et al. [37] seem to assume that the driving behaviours of the two different versions of automated vehicles will stay the same independently of the penetration level. This indirect assumption that there is no correlation between the technological development of AVs and the penetration rate seems to be made in most traffic simulation investigations described in the literature.

Another approach is to consider the effect of AV-human driver interaction in traffic flow simulation with the incorporation of more sophisticated human factors in mathematical models for driving behaviour. van Lint and Calvert [38] and Calvert and van Arem [39] proposed an improved simulation approach for the interactions between AVs and their drivers, and interactions with other human drivers. The framework especially considered the transition of control (ToC) as an important aspect of vehicle-driver interaction for the simulation of automated vehicles. More research is however needed in regard to human factors in driving and vehicle automation to refine the framework.

Do et al. [40] present a literature review of simulation-based investigations of connected and automated vehicles. Most of the studied articles simulate ACC or CACC systems, and for the ones simulating AVs or CAVs, the authors conclude (partly based on the conclusions in Milakis et al. [41]) that the model parameters are not calibrated based on real field data due to that AVs of level 3 or higher are still immature. Furthermore, Do et al. [40] conclude that the different studies use their own assumptions for the capabilities of the automated vehicles which can lead to inconsistencies in conclusions. Hence, "standardized driving characteristics of intelligent vehicles are necessary for future research studies as most studies use different assumptions on the key features of intelligent vehicles" and "the impact analysis of intelligent vehicles is still in a preliminary stage involving many uncertainties" [40].

3. Suggested Approach for How to Represent Different Levels of Automation

There are several uncertainties regarding the introduction of AVs. There are, for example, large uncertainties on how the mix of vehicles with different levels of automation will evolve during the transition period from 0 to 100% automated vehicles. One way of taking these uncertainties into account is to conduct scenario-based analysis.

To investigate the range of conditions that are likely to occur during the gradual introduction of AVs, we define three stages of coexistence: the introductory, established, and prevalent stages. These stages can be complemented by the stages of no automation and full automation. The use of three stages enables limitation of the number of scenarios, while still providing insight into the whole range of the transition period of introduction of AVs. The stages are not defined in terms of specific number of years in the future, but rather by the level of automation in a specific case study. The exact nature of the stages may vary significantly between different road facilities, and all three stages may not be relevant for all road facilities and case studies. Also, depending on many factors, including technological development and adoption rates, and changes to the legal framework, the stages may have vastly differing durations. Hence, defining the stages in terms of time is not only highly speculative but also problematic since the durations of the stages might vary. At a conceptual level, the stages are as follows:

(i) Introductory: automated driving has been introduced, but most vehicles are conventional cars. Automated driving is in general significantly constrained by limitations (real or perceived) in the technology.

(ii) Established: automated driving has been established as an important mode in some areas. Conventional driving still dominates in some road environments due to limitations (real or perceived) in the technology.

(iii) Prevalent: automated driving is the norm, but conventional driving is still present.

The descriptions of the stages above are not quantitative definitions, but rather qualitative descriptions. The quantitative definition of each stage is given by the penetration rates of the various AV classes defined below. When applying the suggested approach for analysing a specific case, relevant uncertainty factors, such as penetration rates and AV mixes, need to be quantified for each stage based on assumptions on the evolution and deployment of AVs for the area of study with respect to the road environment and driving context. The assumptions will be highly uncertain, especially for the later stages. Hence, several versions of each stage with different combinations of penetration rates and AV mixes need to be evaluated in order to obtain a range of simulation results for each stage to illustrate the uncertainty in traffic impacts during the different stages of the transition period. The result ranges may also be used to estimate at what stage one can expect significant benefits from the introduction of AVs.

In addition to handle the penetration rates of automated vehicles during the different stages of the transition period, there is a need to handle the variety of automated vehicles with different levels of automation. One possibility would be to use the SAE (SAE International 2018) levels, but they focus on to what extent the vehicle is driving by itself, where it can drive itself, and who is responsible for the driving. For example, SAE levels 1 and 2 relate to driver support systems that assist in the dynamic driving task, but the driver is responsible for the driving. At level 3, an automation driving system (ADS) performs the entire dynamic driving task but can only operate in some limited operational design domain (ODD) and the driver is responsible for the driving. Level 4 is an extension of level 3 in which the ADS is responsible for the driving. The focus of this article is automated vehicles with level 4 capabilities for some ODDs. However, the SAE levels do not distinguish how the driving behaviour varies between different levels or within a level. Therefore, we suggest that the level of automation is specified by the following two concepts:

(i) AV class (Basic AV, Intermediate AV, and Advanced AV)

(ii) Driving logic (Rail-safe, Cautious, Normal, and All-knowing) for different road environments

3.1. AV Classes. An AV class is a high-level description of the behaviour and capabilities of the vehicles. We assume that the main priority at each class is safety and that difference between the classes lies in the operational design domain (ODD) and how "offensively" the vehicles can handle different road environments and traffic contexts. We think that at least three classes are needed and suggest the following classes as a starting point:

(i) Basic AV: the first type of AVs with SAE level 4 capabilities only for one-directional traffic environments with physical separation with active modes. The behaviour is in general quite cautious and risk minimizing.

(ii) Intermediate AV: AVs with level 4 capabilities in some road environments and driving contexts. The behaviour at more complex road environments and driving contexts is still cautious and risk minimizing while the behaviour at less complex road environments and driving contexts can be less cautious and still be safe.

(iii) Advanced AV: AVs with level 4 capabilities in most road environments and driving contexts. The advanced AVs can drive more "offensively" but still safe in most road environments and driving contexts but still need to apply a more cautious behaviour in complex road environments and driving contexts.

3.2. Driving Logics. While an individual vehicle always belongs to the same AV class, its behaviour changes depending on the infrastructure and traffic conditions; structured environments with physical separation to other modes and directions of travel require less caution than complex environments with multidirectional interactions. That is, a given vehicle can drive more offensively—keep shorter following distance and accept smaller gaps—in highly structured environments like motorways, compared to less structured environments like urban streets or shared spaces. Thus, to specify the driving behaviour of a vehicle of a specific AV class, we need to specify how it behaves at each type of road environment it may encounter. This environment dependence of the behaviour could be specified taking into account details of the local conditions of the specific road link, but that would be prohibitively complex and would impede both model implementation and generalizations of the results. Thus, we propose using a small number of AV driving behaviours, called driving logics, paired with a small number of road types, to specify the environment-dependent behaviour of each AV class.

A basic assumption for all of the driving logics is that automation will lead to a shift in legal responsibility in case of accidents, from the driver to the manufacturer of the vehicle. Since this will lead to an accumulation of responsibility to a relatively small number of developers or corporate executives that will be legally responsible for all accidents of a given vehicle model, there will be strong incentives to minimize the number of accidents that can be seen as caused by the AV from a legal perspective. Thus, all automated vehicles are assumed to strictly follow the road code, and the user cannot, for example, set the desired speed above the legal limit.

The driving logics are given purely functional definitions, that is, the definitions specify the functionality of the vehicles without reference to what hardware or software that enables the functionality. This is an important simplification that allows specifying archetypal behaviours without differentiating based on speculations regarding the technology used to achieve the behaviour. We propose four driving logics: the first two correspond approximately to driving behaviour that have already been implemented in prototype AVs, while the remaining two correspond to possible future milestone capabilities of automated vehicles. We propose the following driving logics:

(i) Rail-safe: the vehicle follows a predefined path for the whole trip and emergency brakes if anything is on the collision course and slows down every time its sensors can have blind angles to avoid surprises. This driving logic is not dependent on communication or cooperation with other vehicles or the infrastructure.

(ii) Cautious: calculates gaps accurately and only merges when gaps are acceptable, and as the Rail-safe logic it slows down due to sensor blind angles. This driving logic is not dependent on communication or cooperation with other vehicles or the infrastructure.

(iii) Normal: uses the logic of an average driver but with the augmented (or diminished) capacities of the sensors for the perception of the surroundings. This type of driving logic may require devices for vehicle communication and cooperation.

(iv) All-knowing: perfect perception and prediction of the surroundings and the behaviour of the other road users. This automated driver is capable of forcing his way on other drivers whenever is needed without however ever being responsible for causing accidents. This type of driving logic requires devices for vehicle communication. If the devices fail, the logic may fall back to the Normal or Cautious driving logic depending on the driving context. With additional communication devices and control logics, the driving logic enables cooperation with other AVs with communication and cooperation functionality.

As indicated by the specifications of the driving logics above, communication is not explicitly modelled, but is for all driving logics except the All-knowing logic regarded as one of many possible technologies that could contribute to produce the specified functionality. For the All-knowing driving logic, however, communication is assumed to be required to achieve the functionality, but it is still not explicitly modelled.

The four driving logics are described in more detail in the following sections.

3.2.1. The Rail-Safe Driving Logic. Motivated by compliance with the machinery directive (Directive 2006/42/EC of the European Parliament and of the Council of 17 May 2006 on machinery, and amending Directive 95/16/EC, ELI: http://data.europa.eu/eli/dir/2006/42/2016-04-20), the Rail-safe (RS) driving logic represents a fail-safe deterministic driving behaviour. The vehicle follows a predefined path from which it cannot deviate, and the speed is set by the guiding principle that it should be able to brake for anything that may come in its way. To guarantee the ability to emergency brake, the brakes are preactuated, as in rolling stock, so emergency braking will be executed even in the case of total power failure. This strategy is safe only up to certain speeds, depending on the restraining systems for the passengers, which significantly limits the top speeds of RS vehicles.

The maximum speed is determined by the distance to other road users and obstacles that blocks the field of view of the vehicle. The maximum speed is set such that the vehicle can brake with an acceptable deceleration for any road user that can reasonably enter its predefined path, including hypothetical road users currently out of view due to obstacles. In particular, this strategy implies the RS vehicle never approaches another road user closer than the "brick wall stop distance" (BWS), that is, the RS vehicle keeps a distance such that it can avoid collision by emergency braking even if the leading vehicle instantly stops.

The full focus on fail-safe operation leads to that the RS logic only can operate efficiently at higher speeds if it has a reserved lane with separation to both neighbouring lanes and sidewalks, in the form of either a buffer area or a physical barrier. Also, it can only cross conflicting streams if it has absolute right of way. Conceived to certify automated shuttle services on public roads together with some European Ministry of Transport, this driving logic is called Rail-safe logic because it follows for certification an approach derived from the rail technical standards as explained in Alessandrini [42]. The example in Figure 1 is an urban multilane arterial with three lanes per direction, unsignalised intersections at grade, and unprotected sidewalks. An infrastructure as such will never be certified for the "Rail-safe" logic but nevertheless is a good example to show what can and cannot be done with this logic and the others. More detailed explanations on how to insert automated road transport systems (ARTS) [43] in urban environments are given in Cignini et al. [44] and Tripodi et al. [45]. In Figure 1(a), the automated vehicle is all alone. It has a full view on the sidewalk, which is empty and can therefore ride at its maximum speed. As soon as a pedestrian is present on the sidewalk, the speed of the vehicle is limited by the time to collision with such "obstacle" that might arise if the pedestrian decides to suddenly cross the street. If the sidewalk is a metre away from the automated vehicle course and a pedestrian walk at a metre per second, the vehicle can only overtake the pedestrian at a speed which would allow it a full stop in one second. If the maximum allowed deceleration is 1.2 meters per square seconds (standing nonrestrained passengers on board), the maximum speed can be 1.2 meters per second (nearly 4.5 km/h), which grows to 18 km/h with sitting and belted passengers on board. To increase the vehicle's speed, the sidewalk needs either to be separated from the road or some safety boundary put between the sidewalk and the automated vehicle lane.

As shown in Figure 1(b), the vehicle cannot change lane and, as shown in Figure 1(c), it cannot turn left. To turn left, the vehicle must have a clearly marked lane (as shown in Figure 1(d)) and a dedicated traffic light without conflicting traffic stream allowed when the automated vehicle passes. Where necessary, this logic forces communication with the traffic lights in the infrastructures and with specially installed roadside sensors to guarantee operations as safe as in rail transport.

3.2.2. The Cautious Driving Logic. In contrast to the guiding principle of the RS logic, which is to do everything to not be involved in an accident, the guiding principle of the Cautious driving logic is to do everything not to *be responsible* for an accident. This implies that it always strictly follows the road code and always is on the safe side when accepting gaps.

Similar to the RS logic, the Cautious logic needs to assume that anything can turn up where its field of view is blocked and that following only can be done at BWS distance. However, in contrast to the RS logic, the Cautious logic assumes that other road users behave reasonably according to the road code; pedestrians are assumed to not suddenly jump out in the road, and vehicles in the neighbouring lanes are assumed not to suddenly cut in in front. Thus, the Cautious logic can handle nonsignalised conflicts, such as crossing or joining a traffic stream with right of way, changing lanes, or even overtaking slow vehicles. However, in all cases, it only acts when gaps are larger than BWS distance to guarantee that it does not cause an accident by conflicting with the prioritized flow.

BWS is not a criterion normally used on the roads; however, it is the only safety criterion which "can be proven safe". The reason for including BWS in the Cautious driving logic is that a vehicle keeping a BWS distance is never at fault in an accident. As discussed in Section 3.2, the legal responsibility in accidents will shift from drivers to makers concentrating responsibilities (especially the criminal one) for many accidents on few designers and company executives, many vehicle makers will want to be sure their vehicles will not be held responsible for causing accidents, and implementing BWS distance keeping would be one possible strategy to strongly reduce the number of accidents where the AV can be seen as causing the accident. Other criteria (for the Normal and the All-knowing driving logics) have been set to consider more normal and aggressive driving behaviours, but for the cautions it was necessary to set a reference which has a specific legal reasoning behind.

In Figure 2(c) the vehicle is allowed to turn left. However, it can do so only if each vehicle in the incoming lane is far enough away so that they do not have to decelerate. Assuming each vehicle will continue with its own speed and given the speed of the automated vehicle when the automated vehicle clears the path of the incoming vehicle, a BWS distance needs still to be in place. Should for any reason the automated vehicle stop in the middle of the crossing, the

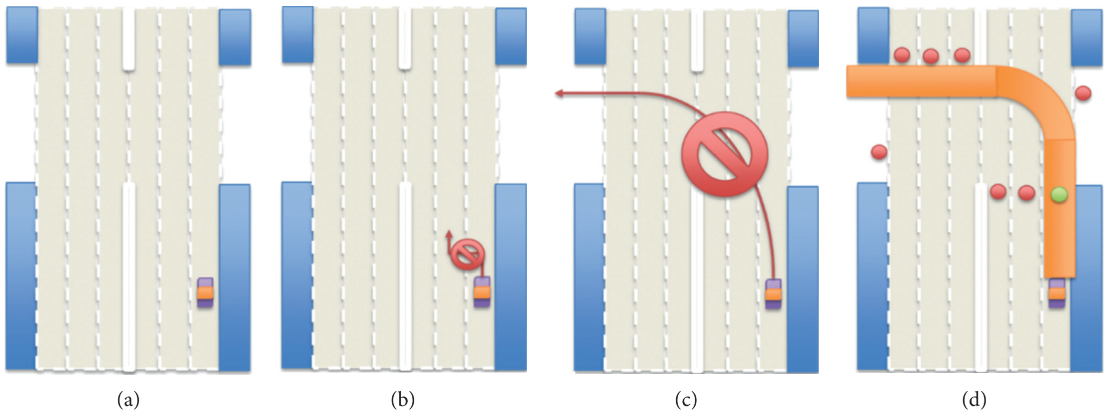


Figure 1: Illustration of the Rail-safe driving logic for road following (a), prohibited lane-changing (b), and left-turning (c). To allow left-turning for a Rail-safe logic, the road needs to be clearly marked and a traffic light inserted with a dedicated aspect for the automated vehicle left-turning which can even turn left from the right lane at this point (d).

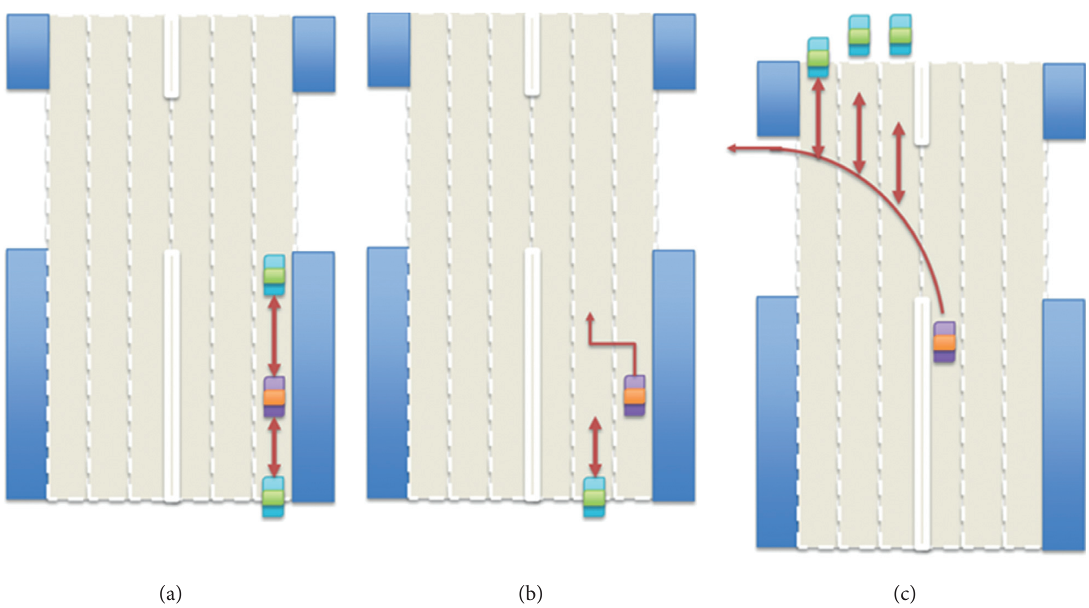


Figure 2: Gap acceptance for car-following (a), lane-changing (b), and left-turning (c) in the Cautious driving logic.

incoming vehicle can still come to a full stop without risking collision with the stopped automated vehicle. In case the automated vehicle passes through the intersection as planned, the incoming vehicle does not need to decelerate.

The case is similar in lane-changing (Figure 2(b)). The lane-changing manoeuvre is considered possible when the automated vehicle has reached the same speed of the flow of vehicles in the lane and the vehicle in the back (at the same speed) still has a BWS distance from the automated vehicles. This leads to the difficulty to conduct lane changes in heavy traffic.

3.2.3. The Normal Driving Logic. The Normal driving logic imitates the general human driver behaviour, but with the advantages and limitations of machines compared to humans, for example, shorter reaction time, more exact measurements of distances and time gaps, and precise execution of intended manoeuvres, but possibly more occlusion of the field of view by dynamical obstacles. However, the Normal driving logic does not imitate unwanted features of human drivers; it complies perfectly with the road code and there is no randomness in its behaviour.

The Normal driving logic is easy to implement in traffic simulation software: the driving logic is modelled using the regular model for conventional driving, but with stochasticity removed, reaction time improved, and occlusion of sensors approximately included. Accepted gaps and following gaps are similar in size to the ones of human drivers, due to that the Normal driving logic has shorter reaction time but lacks some of the predictive capabilities of human drivers.

3.2.4. The All-Knowing Driving Logic. For automation to lead to more efficient, in addition to safer, traffic, a vehicle with the All-knowing driving logic predicts the behaviour of all road users detected by all connected detectors, on both vehicles and the infrastructure. This leads to very few blind spots and massive amounts of data to use as a basis for accurate predictions, which allows the All-knowing vehicle to keep short gaps and even force its way in conflicts when needed to achieve efficient flow, while keeping its manoeuvres safer than most human drivers.

This driving logic is of course much easier to simulate than implement in reality; in the simulation, we know the exact trajectory of all road users and their behaviour, so predicting it is not a problem. In reality, on the other hand, it is completely unknown how this driving logic would be implemented or how hard it would be. The All-knowing driving logic thus represents an extreme case that will not be realized in the foreseeable future.

Lane-changing as shown in Figure 3(b) happens with such small gaps that the following vehicle yields to let it merge as in a sort of cooperative manoeuvre. Left-turning as shown in Figure 3(c) can be done with small gaps and even when some of the vehicles in the furthest lanes are not in sight. Such behaviour can happen either because prediction models are perfect or because there is cooperation between vehicles; however, in simulation, it is not important which is the technology but only the resulting behaviour.

3.3. Assumptions on the Relation between Driving Logics and AV Classes for Road Environments. Simulations of automated vehicles do need to consider not only the driving logic of the vehicle but also the operational design domain (ODD) in which it can operate and according to which driving logic. As noticed in previous research [46], automated vehicles may have to adjust their driving behaviour depending on the road environment and the driving context. In this section, we present initial assumptions on which type of driving logic vehicles of different AV classes would be able to use for different types of vehicles and for different types of road environments. These assumptions were derived based on workshops and discussions between traffic model developers, traffic engineers, vehicle industry, and human factors researchers. It is important to note that these are general assumptions and that they might need to be adjusted depending on information or expectations for a specific case study. In this article, we used the following division and definitions of road environments:

(i) Motorway: multilane roads with physical barriers between directions and grade-separated intersections

(ii) Arterial: single- or multilane roads with at-grade intersections (mainly larger type of intersections as signalized intersections or roundabouts). Bicycle and pedestrian traffic are clearly separated from the vehicle traffic by either physical barriers or medians. Vehicles, bikes, and pedestrian may interact at intersections depending on if secondary conflicts between vehicles and active modes are separated or not.

(iii) Urban street: single- or multilane roads with at-grade intersections (also stop or yield regulated intersection). No physical separation between vehicle traffic and pedestrian and bicycle traffic. Walkways and bikeways directly at the side of the vehicle lanes.

(iv) Shared space: vehicle, bicycles, and pedestrian share the same space, which can be unstructured or semistructured.

Table 1 presents the assumptions for which driving logic cars and trucks will use at the various road environments. Basic AVs are assumed to be able to drive in automated mode only on motorways and arterials. Furthermore, they are assumed to drive according to the Cautious driving logic on these road types. The Intermediate AVs are assumed to be able to use the Normal driving logic on motorways due to the development of sensor technology and anticipatory capabilities. The more complex arterials with at-grade intersections with interactions with active modes still constrain the AVs capabilities, and the behaviour is still according to the Cautious driving logic. Exceptions might be highly separated arterials with total conflict separation between vehicles and active modes, in which Intermediate AVs can be assumed to be able to drive according to the Normal driving logic. Furthermore, the Intermediate AV is assumed to be able to drive according to a Cautious driving logic on urban streets and according to the Rail-safe logic in shared spaces. However, it is questionable to what extent drivers would accept the Rail-safe logic driving in shared space due to the high "politeness" of the driving logic and the resulting low speed. Thus, it might from a traffic simulation point of view be more reasonable to assume manual driving. The Advanced AV class cars are assumed to be able to drive according to at least the Cautious logic in all the road environments, ranging from the All-knowing driving logic on motorways and arterials to the Normal driving logic on arterials and Cautious logic in shared spaces.

4. Implementation of AV Classes and Driving Logics in the Traffic Simulation Model VISSIM

The descriptions of the driving logics in the previous section are of conceptual nature. Further specifications are required to be able to implement the driving logics in a traffic simulation model. As described in Section 2.1, driving logics can be implemented either by replacing behavioural models in the traffic simulation model with automated vehicle driving behaviour models or by adjustment of behavioural model parameters in the traffic simulation model. The approach in this article has been to as far as possible try to adjust the behavioural parameters of the available behavioural models and when necessary extend the currently available models. This approach is chosen in favour of replacing the behavioural models. The idea behind this is that it, from a traffic performance point of view, is more important to capture the main characteristics of different

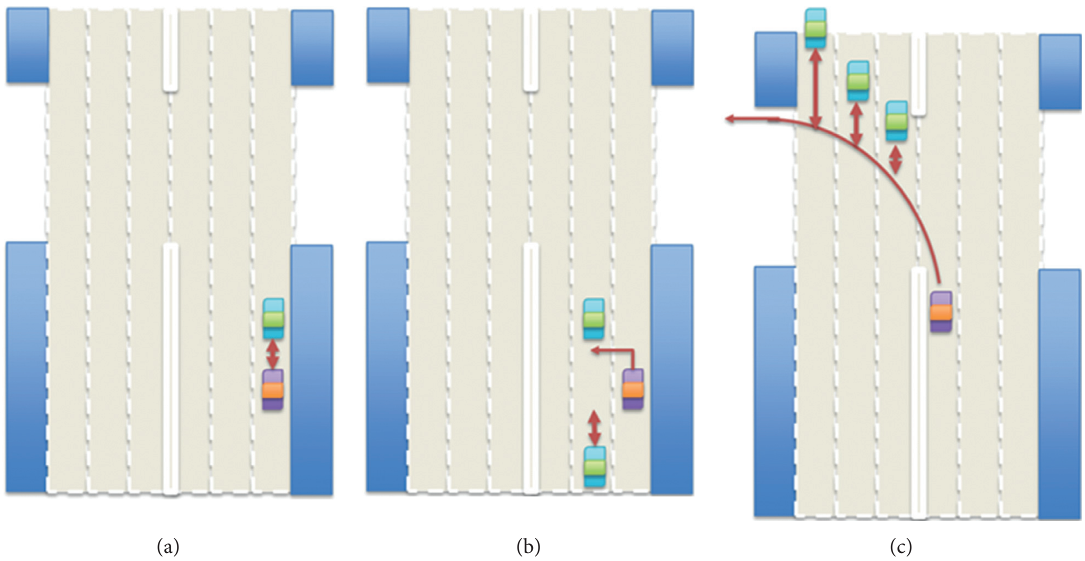


Figure 3: Gap acceptance for car-following (a), lane-changing (b), and left-turning (c) in the All-knowing driving logic.

Table 1: Specification of the driving logics envisioned for the three AV classes in the different road environments for cars.

Road type	Basic AV	Intermediate AV	Advanced AV
Motorway	Cautious	Normal	All-knowing
Arterial	Cautious	Cautious/Normal[1]	All-knowing
Urban street	Manual	Cautious	Normal
Shared space	Manual	Rail-safe[2]/Manual	Cautious

[1]The Normal driving logic will only be possible if all conflicts between vehicles and active modes are separated, e.g., by separate phases in a traffic signal. [2]It is questionable to what extent drivers would accept the Rail-safe logic driving in shared space due to the high "politeness" of the driving logic and the resulting low speed. Thus, it might from a traffic simulation point of view be more reasonable to assume manual driving.

types of automated vehicles instead of modelling all different types and combination of automation functions in detail.

Independently of approach, data for calibration of parameters are required. The Rail-safe and the Cautious driving logics correspond approximately to driving behaviour that have already been implemented in prototype AVs, while the Normal and All-knowing logics correspond to possible future milestone capabilities of automated vehicles. Hence, data from field test of current AV concepts can only be used to some extent to calibrate the suggested driving logics. We have therefore combined the data from field trials and cosimulations, which can give some information about currently available driving logics, e.g., with respect to following behaviour, with assumptions based on the conceptual descriptions of the driving logics presented in Section 3.2.

4.1. Results from Test-Track Tests with Automated Vehicles with TNO's Driving Logic. Within the CoEXist project, a test-track field test using CAV prototypes developed by TNO was conducted. Three vehicles were used in the field test, one with ACC, one with Cooperative ACC (CACC), and one with Degraded CACC (dCACC). Several different scenarios with different combinations of behaviour of the three vehicles in a platoon were tested (see example in Figure 4). In the example, the first vehicle is driven by a human, the second by an ACC-controlled vehicle, and the third by a CACC-controlled vehicle. Two different cases are shown: one in which the communication with the second vehicle regarding relative position and speed is on and then when it was turned off.

In this section, we summarize the key findings of this data collection, and the full details of the design, execution, and results are available in Sukennik et al. [47]. The key findings from the experiments are listed below. These findings might not be generalizable to all types of cooperative vehicle-following systems but may apply only to the specific control strategy that the test vehicles used in this research. However, it is always difficult to sustain that any conclusion is universally valid when most of the automated driving technology which needs to be implemented in the traffic simulation model is still to be developed.

(i) There is a linear deterministic relationship between headway and speed when an automated car is following another automated vehicle with car-to-car (C2C) communication. Human imperfection while driving is replaced by higher precision and deterministic nature of technical equipment and algorithms.

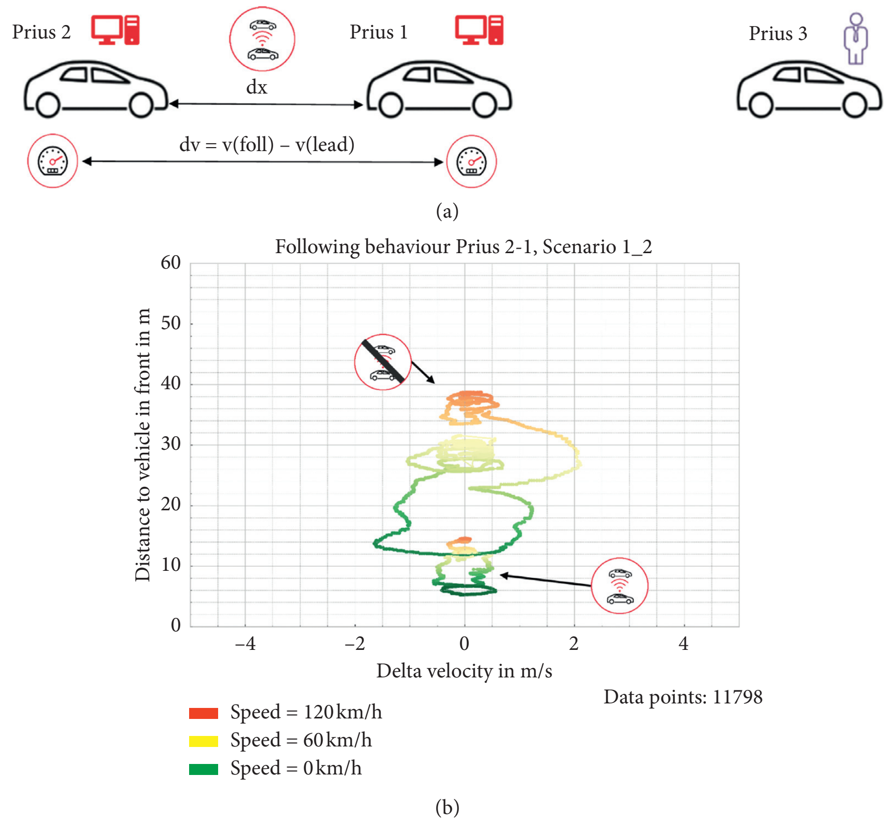


Figure 4: Relationship between speed difference and distance to preceding vehicle when following.

(ii) There is an almost linear relationship between headway and speed when an automated car is following a manually driven car or an automated car without C2C communication. The linear relationship is not as neat as with C2C communication but could be approximated.

(iii) Oscillations during the following process are small and without much variance in comparison with human drivers.

(iv) Safety distance without C2C communication is much higher than in the communication case: with C2C communication, the test vehicles were able to drive safely with a 0.6- or 0.3-second headway. After the disconnection of the C2C communication, the vehicle adapted larger following distance because of safety reasons.

(v) The safety distance in drive-away behaviour is larger when there is no communication. When following from standstill, the test vehicle kept a significantly larger safety distance in the case without C2C communication than with C2C.

(vi) No stochastic variation in drive-away behaviour.

(vii) When an automated vehicle followed another vehicle from a standstill (in front of a signal head), the following process did not show stochastic variations—the same behaviour applied each time.

4.2. Parameter Changes in Vissim and Added Modelling Concepts. The AV classes described in Section 3.1 are implemented in Vissim in a common way similarly as conventional vehicles. Each link representing a road segment is coupled with a link behaviour type. For a link behaviour type, the modeller can specify a driving behaviour for each vehicle class.

The driving logics are implemented in Vissim as new driving behaviours based on the Wiedemann 99 [48] driving behaviour model. The Wiedemann model operates at small reaction times (each time step) and takes oscillation in car-following into account (as observed by AVs in Figure 4). This is important for modelling AVs. But the model also accounts for psychological aspects as well as for physiological restrictions of drivers' perception of what we do not expect from AVs driver logics. Therefore, an extension to the model is required to model the behaviour of AVs as observed in Section 4.1. The contribution to the model results in these new features to allow for fundamental principles needed to model the AV driving logics:

(i) Reduction of implicit stochastic: the option "use implicit stochastic" can now be switched off for a specific driving behaviour. A vehicle using this driving behaviour does not use any internal stochastic variation, which is meant to model the imperfection of human drivers. For all distributions that cannot be explicitly set by the user, a median value is used instead of a random value.

(ii) Brick wall stop distance: the option "enforce absolute braking distance" can now be activated for a specific driving behaviour. Vehicles using this driving behaviour will always make sure that they can brake without a collision, even if the leading vehicle comes to an immediate stop (turns into a brick wall). Brick wall stop (BWS) distance is maintained by vehicles with the Rail-safe and Cautious driving logics.

(iii) Differentiable following parameters based on the leader vehicle class: this allows to set different headways for CAV following another CAV as for CAV following conventional vehicle or for any other combination of vehicle classes. This feature is applicable for driving logics such as the All-knowing logic which is based on the vehicle capability to recognise the leader vehicle class in the following process.

(iv) Sensors/equipment limitations: number of objects and vehicles that the vehicle can see and interact with can be defined separately for each driving logic. The number of interaction vehicles defines an upper limit for the observed leading vehicles; therefore, for example, this could be set to 1 for automated vehicles with a sensor equipment that cannot see through the leading vehicle. A red signal downstream of the leading vehicle could still be observed, but not the second real vehicle downstream.

The findings from the field trials in combinations with calibrations of the Wiedemann 99 model to the field trial vehicle trajectories were used to estimate parameters for the following behaviour in Vissim (see Table 2). To describe a more deterministic behaviour, the oscillation-related parameters are "turned off" expect that some minor acceleration oscillations are kept. The more advanced logics (e.g., Normal and All-knowing) possibilities to keep shorter gaps are implemented using the three following gap-related parameters (CC0, CC1, and CC3). Acceleration rate-related parameters are adjusted to reflect the more cautious behaviour of the Rail-safe and Cautious driving logics and the more offensive behaviour of the All-knowing logic.

Since no field data were available for adjustment of the lane-changing behaviour parameters, these are adjusted based on the conceptual descriptions of the driving logics according to Tables 3 and 4. Maximum and desired accepted deceleration rates follow the same pattern as for the car-following acceleration-related parameters. Hence, the Cautious driving logic does not accept as high deceleration rates as a consequence of a potential lane change. The parameter "$-1\ \mathrm{m/s^2}$ per distance" affects the distance at which a driver starts to accept higher deceleration rates than the desired acceleration rate for accepting a gap in the target lane. The Cautious driving logic is assumed to start accepting higher deceleration rates later while the Normal and All-knowing would behave similarly to a human driver in this matter.

Table 4 presents the parameter values related to cooperation and gap acceptance in connection with lane changes. The Normal logic is assumed to follow a human driver while the Cautious logic requires a larger minimum headway, less reduction of safety distance, and lower deceleration rates for cooperation.

In addition to the car-following and lane-changing parameters, AVs are assumed to drive more homogeneously compared to human-driven vehicles in terms of individual speeds and acceleration/deceleration behaviour. Desired speed distributions for AVs are assumed to be narrow and concentrated around the speed limit since the AVs are assumed to follow the road code. Individual settings of desired speeds may be possible for lower SAE levels (as driver support systems or conditional automation), like in today's automated cruise control vehicles, where the driver still is responsible for the driving. However, as discussed in Section 3.2, we assume that the producer of the vehicle will get increased legal responsibilities at SAE level 4 and we therefore assume complete compliance with the road code.

Furthermore, it is expected that automated vehicles will behave deterministically instead of stochastically like human drivers, which might have implications on the acceleration and deceleration behaviours. Therefore, all AVs are assumed to have the same maximum and desired acceleration and deceleration values. Different types of AVs or different vehicle brands might of course apply different acceleration rates in similar situations. However, when operated in automated mode, the utilized acceleration and deceleration rates will need to be constrained by comfort and safety requirements of the passengers, which lead to the assumption that the acceleration behaviour of automated vehicle will be very similar.

Moreover, the perception capabilities of the different driving logics are considered by limiting the number of vehicles ahead taken into account to one vehicle for the Rail-safe, Cautious, and Normal driving logics. Reactions on signals are assumed the same for all AV driving logics and the main differences compared to human drivers are that the AVs require full safety distance in interaction with other vehicles and that they only start passing the signal when it is green (red-amber is interpreted as stop). The AVs are assumed to have no reaction time while the reaction time of the human drivers depends on site-specific calibration. In the example simulations presented in Section 5, humans have zero reaction time.

5. Numerical Experiments

To illustrate the effects on traffic performance of the different driving logics, a set of simulations was conducted and results in form of maximal throughput and fundamental diagrams were produced. Here we present simulations of four different networks representing basic traffic situations:

(1) A simple one-lane link under ideal conditions without influence of intersections, parking manoeuvres, or other sources of disturbance

(2) A two-lane motorway without on- and off-ramps but with varying uphill gradient (from 0 to 3.4%)

Table 2: Recommended driving behaviour parameters for following in Vissim.

Parameter (Wiedemann 99 following model)**	Driving logic				
	Rail-safe	Cautious	Normal	All-knowing	Def***
CC0—standstill distance (m)	1.5	1.5	1.5	1	1.5
CC1—spacing time (s)	1.5*	1.5*	0.9	0.7****	0.9
CC2—following variation (m)	0	0	0	0	4
CC3—threshold for entering “following” (s)	−10	−10	−8	−6	−8
CC4—negative “following” threshold (m/s)	−0.1	−0.1	−0.1	−0.1	−0.35
CC5—positive “following” threshold (m/s)	0.1	0.1	0.1	0.1	0.35
CC6—speed dependency of oscillation (10^{-4} rad/s)	0	0	0	0	11.44
CC7—oscillation acceleration (m/s^2)	0.1	0.1	0.1	0.1	0.25
CC8—standstill acceleration (m/s^2)	2	3	3.5	4	3.5
CC9—acceleration at 80 km/h (m/s^2)	1.2	1.2	1.5	2	1.5

*If “enforce absolute braking distance” is on, brick wall stop distance is guaranteed. **See Vissim manual [48] for detailed description. ***Default values for Wiedemann99 following model in Vissim (conventional vehicles). **** If the followed vehicle is a conventional one, the follower maintains 0.9 s spacing time.

Table 3: Recommended driving behaviour parameters for necessary lane change in Vissim.

	Driving logic—urban (motorway if the value differs)									
	Rail-safe		Cautious**		Normal		All-knowing		Def	
Parameter for necessary lane change*	Own veh	Trailing veh	Own veh	Trailing veh	Own veh	Trailing veh	Own veh	Trailing veh	Own veh	Trailing veh
Maximum deceleration	n.a.	n.a.	−3.5	−2.5	−4	−3	−4	−4	−4	−3
−1 m/s^2 per distance	n.a.	n.a.	80 (160)	80 (160)	100 (200)	100 (200)	100 (200)	100 (200)	100 (200)	100 (200)
Accepted deceleration	n.a.	n.a.	−1	−1(−0,5)	−1	−1 (−0,5)	−1	−1.5 (−1)	−1	−1 (−0,5)

*Necessary lane change means a lane change which is necessary in order to follow a defined route (it is not overtaking because of higher own desired speed). ** If “enforce absolute braking distance” is on, brick wall stop (BWS) distance is guaranteed. n.a. = not available.

Table 4: Recommended driving behaviour parameters for lane change in Vissim.

Behavioural functionality	Driving logic				
	Rail-safe	Cautious**	Normal	All-knowing	Def
Advance merging*	n.a.	On***/off	On***	On	On
Cooperative lane change*	n.a.	On***/off	On***	On	Off
Safety distance reduction factor	n.a.	1 + EABD	0.6	0.75	0.6
Min. headway (front/rear)	n.a.	1	0.5	0.5	0.5
Max. deceleration for cooperative braking	n.a.	−2.5	−3	−6	−3

*Depends on technical equipment and implemented connectivity and cooperation functions. **EABD (enforce absolute breaking distance) must be on. ***If the AV cannot detect that the other vehicle wants to change lanes, the value should be off/zero. n.a. = not applicable.

(3) A three-lane motorway section with one on-ramp and one off-ramp

(4) A one-lane approach to a traffic signal (considering only one approach)

The networks were populated with different shares of vehicles using one of the AV driving logics Cautious, Normal, and All-knowing at the time or a combination of those. The remaining shares of vehicles were simulated as human-driven vehicles using calibrated parameters (motorway networks with interchange and road with gradients) or the default parameters (models with simple link and link with signal) in Vissim. In case of combinations of different AV driving logics, the shares between the AV driving logics are equally distributed. For example, in case of 50% AV penetration rate for a combination of AV cautious and AV normal, 50% of the vehicles are human-driven vehicles, 25% use AV cautious, and 25% use AV normal. Simulations of the Rail-safe logic were not conducted since the logic mainly is applied to minibuses and shuttles which commonly do not reach high penetration rates of all vehicles on the road. To observe the impact of the driving logics compared to human-driven vehicles in terms of throughput, penetration rates (which equals the proportion of AVs compared to all vehicles in the simulation) of 10% steps from 0 to 100% are simulated. For each driving logic and penetration rate, several simulations with eight different demand configurations were conducted. For each combination of driving logic, penetration rate, and demand category, we run 10 simulations with different random seeds. Initially, the resulting relations between flow, density, and speed were then curve fitted to the functional relation by van Aerde [32]. However, the curve fitting was not appropriate at some locations of some networks because no breakdowns occur in

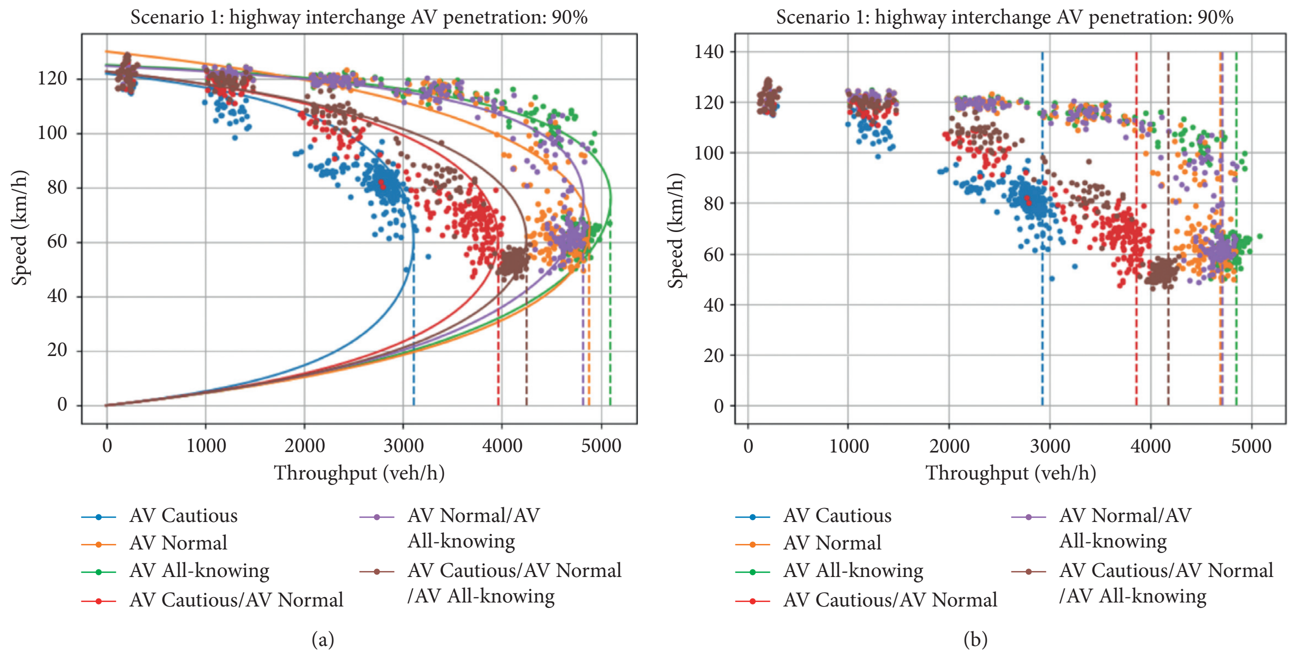


Figure 5: Example of van Aerde diagrams (a) and the 95% quantile (b) for the flow-speed relationships derived from simulations of a two-lane motorway with a one-lane off-ramp and on-ramp for an AV penetration rate of 90% of either the Cautious, Normal, All-knowing, and combined logics. For cases with mixes of driving logics, the shares of the AV logics are equal, e.g., 50/50 and 33/33/33.

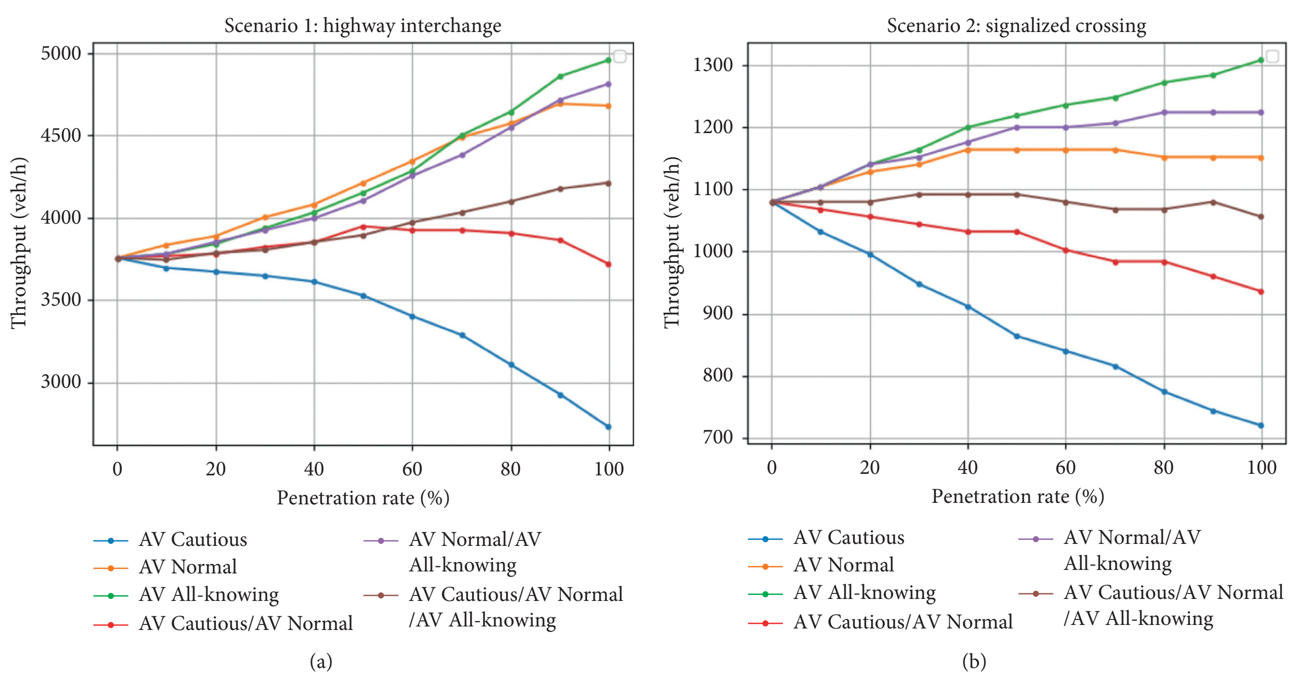
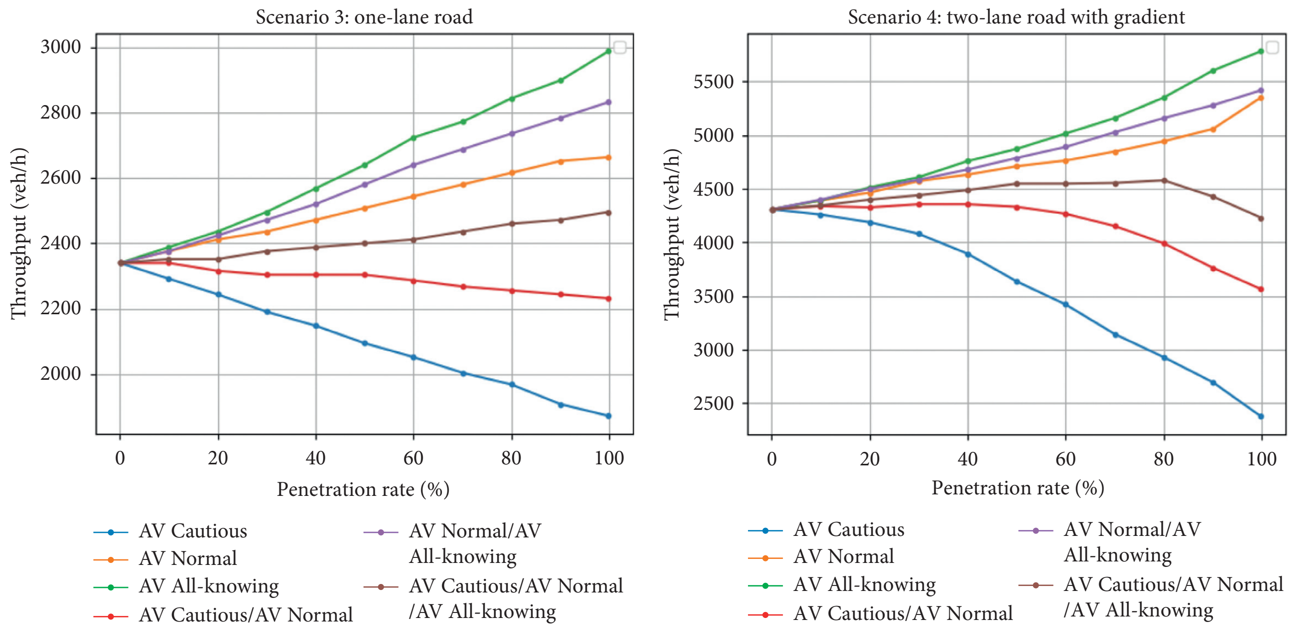


Figure 6: Continued.



(c) (d)

Figure 6: Results in maximum throughput depending on the AV penetration rate and driving logic mix for four different networks: gradient, simple link, on-off ramp and signal, and the AV driving logics: Cautious, Normal, and All-knowing. In the cases with a mix of driving logics, the shares of the AV logics are equal, e.g. 50/50, and 33/33/33.

the simulations with automated vehicles, e.g., for the one-lane road, the bottleneck is already at the inflow of the simulation network and traffic does not break down. Therefore, we derived the capacity not from van Aerde (Figure 5(a)) but from the 95% quantile of all demands (Figure 5(b)). The capacity derived from van Aerde is similar to the 95% quantile of all demands for the scenarios where we observed breakdowns as seen in Figure 5.

Figure 5 shows flow-speed for one of the networks used for numerical experiments (two-lane motorway with a one-lane off- and on-ramp) and one selected AV penetration rate (90%). There is a significant difference between Cautious logic and the other two (Normal and All-knowing). The Cautious driving logic shows lower maximum throughput and lower average speed at the same volume in comparison with the other two behaviour logics. That is because the Cautions driving logic follows the brick wall stop distance requirement for following and also for lane-changing. The All-knowing driving behaviour with settings corresponding to higher aggressiveness does not lead to high improvement because of causing disturbances in mixed flow with lot of lane change maneuverers. Higher gains with All-knowing behaviour logic would be theoretically possible with higher level of cooperation, which was not implemented in the model.

Figure 6 shows the results in maximum throughput depending on the penetration rate for the four different networks and for the Cautious, Normal, and All-knowing driving logics and for equal combinations (mixes) of these driving logics. Because of a larger headway compared to conventional vehicles, the throughput of the Cautious driver logic decreases with increasing penetration rate and on contrary because of the shorter headway, the All-knowing driver logic increases the throughput with increasing penetration rate. The Normal driving logic, where the headway is similar to conventional human-driven vehicle behaviour, increases the throughput with increasing penetration rate. This is because of a more consistent behaviour of AVs compared to conventional human-driven vehicles with less differences in individual behaviour. All-knowing behaviour logic brings an even higher increase in throughput in tested networks, except the highway scenario (motorway with off- and on-ramp), where the Normal and All-knowing driving logic and their combination lead to similar values, especially with penetration rates under 80%. As mentioned before, the number of lane-changing maneuverers and resulting disturbances in the traffic flow are the limiting factors. Further experiments with more varied mixes of conventional and automated vehicles with different driving logics are planned for the end phase of the CoEXist project.

6. Conclusions and Further Development Needs

There exist several uncertainties related to vehicle fleet composition during the transition period from 0 to 100% automated vehicles, e.g., regarding what automation functions are technically feasible, allowed, and actually activated by the users, for different road environments and at different stages of the introduction of AVs. In addition, we can also expect all these factors to be highly heterogeneous over the vehicle population, due to various functions being available for different brands and price levels, for the different times of production of the vehicles in the fleet. Hence, traffic simulation investigations of the transition period need to consider that different types of automated vehicles with different capabilities and behaviour will exist and maybe coexist. Some possible heterogeneities, such as the possible heterogeneity in acceleration behaviour of AVs, have been simplified away in the presented model, which may impact the particular simulation results through effects on lane-changing behaviour. However, the proposed framework for handling uncertainties can in principle be extended to incorporate any and all uncertainties in the behaviour of the simulated road users, including any uncertainties in the heterogeneity of the acceleration behaviour, if this is deemed important for the considered application.

In this article, we present four conceptual descriptions of four different types of driving behaviour of automated vehicles and present how these driving logics can be implemented in a commonly used traffic simulation program. The idea behind the conceptual driving logic approach is that the information available so far on AV behaviour comes from tests with today's partly automated vehicles, mainly from test tracks. How future generations of AVs will behave will be unknown for some time. Thus, investigations of future traffic situations with future versions of AVs and with higher penetration rates of AVs require consistent assumptions on how the behaviour of AVs will evolve. The development and implementation of the four driving logics is one way of dealing with this issue. Furthermore, we believe that it is from a traffic performance point of view more important to capture the main characteristics of different types of automated vehicles instead of modelling all different types and combination of automation functions in detail, which are not available yet in real traffic.

To regard all uncertainties related to the introduction of automated vehicles as independent in a traffic simulation investigation would be infeasible in practice due to the curse of dimensionality; the number of simulation experiments required would become too large. We therefore suggest a simplified treatment of the uncertainties related to the vehicle fleet evolution by assuming that the penetration rate of AVs and the availability of advanced automation functions and driving logics covary and that they become available first for highly separated environments like motorways and later for more complex environments, such as urban streets. These assumptions allow us to constrain the space of possibilities in need of exploration to the vicinity of what we believe to be the most likely development. Furthermore, we suggest to divide the transition period into three stages: introductory, established, and prevalent. The stages are not defined in terms of specific number of years in the future, but rather by the level of automation in a specific case study. The reason is that depending on many factors, including technological development and adoption rates, and changes to the legal framework, the stages may have vastly differing durations. Hence, defining the stages in terms of time is not only highly speculative but also problematic since the durations of the stages might vary.

The developed approach for simulation of different driving logics taking into account their expected ODD and penetration rates for different stages of the transition period will in further work be applied to several different case studies in order to investigate the impact of the introduction of automated vehicles in, for example, signalized intersections, motorways, urban arterials, roundabouts, and shared spaces.

An important simplification in the approach presented here is that we do not consider the handover between automated and manual driving, even though we implicitly assume that such handovers are taking place. Hence, we assume that a specific simulated vehicle operates as either automated or human-driven. However, a vehicle might change driving logic when going from one type of road to another, and only then. Furthermore, this work does not consider potential behavioural adaptation of human drivers due to the introduction of automated vehicles, but this is an important uncertainty that needs to be addressed in future research. Since data availability on potential behavioural adaptation is limited, our suggestion is to conduct sensitivity analysis given different assumptions (e.g., regarding the adaptation of desired speed, following time gap, and overtaking willingness) [49].

Data Availability

The data from the test-track tests with automated vehicles with TNO's driving logic (Section 4) is proprietary data of Siemens/TASS. The data from the numerical experiment (Section 5) can be reproduced using PTV Vissim (version 11 and higher) software with the defined driving logics (Section 4.2). Simulation results are available on request from Peter Sukennik or Jochen Lohmiller.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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