

A generic multi-level framework for microscopic traffic simulation with automated vehicles in mixed traffic

Calvert, Simeon; van Arem, Bart; van Lint, Hans

DOI

[10.1016/j.trc.2019.11.019](https://doi.org/10.1016/j.trc.2019.11.019)

Publication date

2020

Document Version

Accepted author manuscript

Published in

Transportation Research Part C: Emerging Technologies

Citation (APA)

Calvert, S., van Arem, B., & van Lint, H. (2020). A generic multi-level framework for microscopic traffic simulation with automated vehicles in mixed traffic. *Transportation Research Part C: Emerging Technologies*, 110, 291-311. Article TRC2522. <https://doi.org/10.1016/j.trc.2019.11.019>

Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

A generic multi-level framework for microscopic traffic simulation with automated vehicles in mixed traffic

S. C. Calvert*, B. van Arem and J.W.C. van Lint

Delft University of Technology, department of Transport & Planning, The Netherlands.

**Corresponding author*

Abstract- With an increasing number of automated vehicles (AV) appearing on roads and interacting with conventional traffic, there is a need for improved simulation approaches to replicate and forecast the resulting effects. Interactions between AVs and their drivers, and interaction with other human drivers involve new types of complex behavioural processes. There is an increasing necessity to explicitly incorporate these human factor processes in simulation, which cannot be properly accounted for with most current models. In this paper, we present an extended conceptual simulation framework based on human factors processes and applicable for automated driving that does this. The framework makes use of previously constructed constructs to include the effects of driver task demand, situation awareness and fundamental diagrams of task demand to extend to automated driving. This is especially considered for the case of transition of control (ToC), as an important aspect of vehicle-driver interaction. The framework is demonstrated in two experimental cases that consider different ToC situations and is found to be face valid within the applied assumptions. Challenges remain in regard to a lack of quantitative evidence from traffic psychology, automated vehicle dynamics & control and human-vehicle interaction. With increasing amounts of research on-going in these areas, the extended framework will act as a valuable approach to further study and quantify the effects of AVs in mixed traffic in the future.

Keywords: traffic simulation; automated driving; vehicle automation; human factors

1 Introduction

1.1 Research motivation

Accurate traffic models are of paramount importance for a wide range of purposes as national and local government, authorities and researchers attempt to understand the impacts of many future transport developments. A major current development in vehicle technology that will affect future traffic is vehicle automation. Many of the main effects of vehicle automation will occur in the interaction between human drivers and automated vehicle and the interaction between these vehicles with other road users. To be able to forecast and scale up the effects of vehicle automation, simulation is required that can reproduce these human driver interactions with the vehicles. This is the problem we aim to tackle in this paper, in presenting an extension for automated vehicles to a driver behaviour focussed microsimulation framework that will allow realistic human driving behaviour and automated vehicles to co-exist and interact in a valid manner.

Traffic flow modelling has existed for well over half a century, with many types of simulation models being proposed and developed from stimulus-response, to safe-distance, and psychophysical type models to name just a few (van Wageningen-Kessels et al. 2015). Just about all these models have in common that there is some kind of control system; i.e. driver-vehicle units react to a certain stimulus from specifically annotated state variables. The control rules are different per model and represent the main phenomena caused by human drivers, such as congestion waves, capacity drop etc. Much of the implemented driving behaviour is implemented at a generic driver-vehicle level, rather than individual influences on driver performance from a more human factors perspective (Saifuzzaman et al. 2017). In practice, a driver interacts with their vehicle physically, such as pressing the brake and steering, but the driving task also includes a cognitive level, such as observing surroundings, processing information and making decisions (Endsley 1999; Fuller 2005). These aspects of human driving are generally not explicitly considered in most traffic simulation models, and to be honest it is normally not required. Proper calibration of a model with the generic behavioural patterns is often sufficient to perform simulation based forecasts. However, when considering intermediate levels of automation in which a human driver is partially in control, the aspect of real human driving behaviour plays a much greater role (Bellet et al. 2012; Gold et al. 2013; Hoogendoorn et al. 2014; Saffarian et al. 2012). The main reason for this relates to the increased and divergent interactions that drivers have with their partially automated vehicle and the demands that are put on driver's cognitive ability to remain in the loop (Saffarian et al. 2012). These cognitive processes do not have a generic description that can easily be included in a traditional simulation model. A good example of this is the case of transition of control between AV and driver, although many other situations and phenomena exist with vehicle automation (Casner et al. 2016; De Winter et al. 2014; Saffarian et al. 2012). There are many mechanisms that originate from a driver's cognitive processing of information that are too divergent and seemingly random, unless described in the context of the underlying mechanism in greater detail, to be captured in a single distribution of reaction time for example (Saffarian et al. 2012). By describing these processes explicitly by including a direct mechanism to human factors, the effects on driving can be replicated much more accurately and validly.

Driving behaviour research, and of human behaviour in a broader sense, has continued to develop in past decades (Fuller 2005; Pipes 1953; Teh et al. 2014). While there is a general understanding of various parts of human behaviour from a cognitive psychological viewpoint, much of it is still not well understood and certainly has little proven generic and generally accepted theory (Wickens et al. 2015). This adds a further difficulty when attempting to incorporate such a level of human (driving) behaviour in a 'quantitative' simulation model. Recent work by van Lint et al. (2018), and others such as Saifuzzaman et al. (2017), offer frameworks that attempt to explicitly and endogenously consider human behaviour from such an approach. They offer a good starting point for further development of traffic simulation that can consider human behaviour endogenously in a modelling environment

with both AVs and Human Driven Vehicles (HDV), and interactions and transitions between automation. Also, further ongoing developments in understanding and gathering evidence on human behaviour in and with various types and levels of AVs from Field Operational Tests (FOT) and driving simulator experiments, offer opportunities to be able to calibrate and validate traffic simulation models that wish to include mixed AV-HDVs scenarios.

1.2 Objectives and constraints

We argue that it is imperative that simulation models that consider AVs in mixed automated-human traffic must also explicitly and endogenously consider real human driving behaviour. Therefore, following these recent developments in traffic flow modelling and the ongoing developments in driver psychology and human factors, we propose a novel extension to these models that allows both automated and conventionally driven vehicles to be collectively considered in mixed traffic, making use of explicit and endogenous human driving behaviour for driving and interaction with AVs. This contribution focusses on the interactions in mixed traffic and therefore explicitly considers one of the important aspect of initial automated driving, namely that of transition of control.

Throughout this paper, we will describe vehicle automation in two main categories: low and high automation. *Low automation* refers to level of automation in which the driver has an active role and aligns to Society of Automotive Engineers (SAE) levels 1-2 (SAE 2018), while *high automation* refers to levels in which a vehicle can drive autonomously under certain conditions and aligns to SAE level 4-5. SAE 3 lies in between these two descriptions and can be considered as *partial automation*, as the driver has an active and continuous role of monitoring, while the vehicle does drive autonomously on the road and conditions that are permitted. Furthermore, we are well aware of the importance of vehicle cooperation as a necessary component to achieve many of the traffic flow and safety gains that are expected with cooperative and automated driving (Shladover 2009). However, as significant levels of cooperative driving are not expected until after the initial implementation of automated driving (Calvert et al. 2017; Sanchez et al. 2016; Sjoberg et al. 2017) and as the level of complexity from the new approach in this paper to modelling is already high, we aim to first introduce the main principles in regard to vehicle automation. The paper is written with the objective to demonstrate a proof of concept of the application of the automated driving through cognitive processes in microsimulation. We see this as a start of a longer process that will require additional human factors and other empirical evidence to further the future modelling developments.

1.3 Research approach and organisation

The research approach taken in this paper is as follows. In Section 2, we summarise current practice in regard to traffic simulation and vehicle automation, as well as the influence of human factors in vehicle automation and how this plays an important role that should be considered in simulation. This leads us to conclude the main aspects of traffic simulation that currently lack and are in part addressed in this paper. The proposed simulation framework is presented in Section 3. The framework is based on earlier work on human factors in traffic flow simulation, and is now extended to include AV explicit driving characteristics, such as full automated driving, driver intersections with automated systems, transition of control, etc. Each part of the framework is described. To demonstrate the workings of the framework, a demonstrative study case considering different types of transition of control is presented in Section 4. Thereafter, we perform a discussion of the framework and case, and then draw our conclusions.

2 Microsimulation with automated vehicles

In this section, we describe the important areas that require attention for the development of traffic simulation models involving automated vehicles (AV). This includes an overview of current practice and aspects relating to human factor consideration in traffic modelling. We conclude this section

with a summary of the main conditions and constraints that we consider necessary when developing new simulation models for the consideration of automated driving and human-AV interaction.

2.1 Traffic simulation and automated driving

In general, most microscopic models describe the dynamic movements of vehicles by means of acceleration and deceleration of each driver-vehicle combination (Kesting et al. 2007) and using rule-based modelling for lateral movements, such as lane changes. The movements in car following behaviour are described by some function that responds to specific stimuli and by different ranges of descriptive and (partial) explanatory power for the resulting phenomena (van Lint et al. 2018). Examples of these models are: the *safe-distance models* that assume that drivers maintain suitably long enough headway to accommodate braking by leading vehicles, e.g. (Laval et al. 2010; Newell 2002); the *optimal velocity models* that assume that drivers maintain a desired speed and always incline to that speed, also considering their headway to other vehicles, which could see car following at a lower speed (Bando et al. 1998; Davis 2003); *stimulus-response models* that assume an acceleration response to a set combination of different stimuli, such as desired speed, relative speed, and time headways (Gazis et al. 1961; Kerner et al. 2006; Treiber et al. 2000). With a realization that the traditional method of modelling can be rigid and absent of human heterogeneity, which is explicitly present in the way humans drive, advances were made in including some random heterogeneousness in driving behaviour to replicate this aspect of human driving. The earliest examples included the psycho-spacing models (Fritzsche 1994; Wiedemann 1974), which include driver inertia over reactions to a models state variables. Later on, models which included anticipation and delayed response aspects to mimic imperfect driving also started to appear, e.g. (Saifuzzaman et al. 2014; Treiber et al. 2000). Even with a greater inclusion of driver heterogeneity in modelling, there is a strong case to state that these models still make use of exogenous rules and mechanisms to reproduce empirically observable driving behaviour (van Lint et al. 2018).

Simulation of automated vehicles has logically been approached from a similar starting point to mainstream traffic simulation. A general assumption is made that AVs can also be captured by specific rules and mechanisms, and modelled using existing simulation approaches in which behavioural variation is less present (Klunder et al. 2009; Xiao et al. 2017). We would agree with this assumption and moreover state that the many current simulations models actually model AVs more accurately than they do human drivers. The main differences between HDVs and AVs are often depicted by differences in parameter settings of the models (Kesting et al. 2007; Milanés et al. 2014). While some characteristics of AVs can indeed be derived to specific differences in vehicles capability, such as low reaction times or high acceleration and deceleration rates, their general inherent behaviour is not always be the same. Bellet et al. (2012) states that to support human-centred design of automation, new simulation tools are required, from realistic AV simulators allowing full-scale immersive tests, to traffic flow simulations including realistic human driver models that are able to predict the road safety effects of AVs. Such simulation models require an intrinsic understanding and representation of the human factor processes to be able to accurately replicate them in models. To do that, they must embrace cognitive modelling and simulation of human drivers (Bellet et al. 2012; Kyriakidis et al. 2017). Research in the direction of human factor based simulation cautiously started at the start of the millennium, as researchers aimed to make a crossover from psychology towards driver behaviour in simulation (Hoogendoorn et al. 2014; Kyriakidis et al. 2017; Saifuzzaman et al. 2014). Some approaches have made of use of prospect theory to include the aspect of risk and human perception (Hamdar et al. 2008; Hamdar et al. 2015), while the majority of psychological approaches have focussed on reproducing some part of the cognitive processing of information in relation to physical performance of tasks through Fullers' Risk Allostasis Theory (Fuller 2011). These describe the process of task processing and as part of the Task Capacity Interface (TCI) (Cacciabue et al. 2010; Hoogendoorn et al. 2014; Saifuzzaman et al. 2017) and in some cases expand this further to include further aspects of human behaviour (van Lint et al. 2018), such as described through Situational Awareness.

2.2 Role of Human Factors in vehicle automation

While attempting to replicate AVs and HDV-AV interaction, there is also a challenge to actually identify what many of these processes actually entail. Driver-vehicular differences and differences between HDV and AVs have been investigated in various literature (Parasuraman et al. 2000; Calvert et al. 2019a). In HDVs, control of a vehicle is fully in the hands of the driver and all dynamic movements are directly the consequence of the process of human perception - cognitive processing - decision making - and action within the physical limits of the vehicle (Calvert et al. 2019a). In highly automated vehicles (SAE 3-5), the entire process is performed by the vehicles perception sensors (e.g. LIDAR, RADAR, etc.), automated driving control systems (ADCS), and the vehicles own actuation. The behaviour of the vehicles is therefore a direct consequence of the way it is programmed in the ADCS and the quality of the sensing equipment and actuation. On their own, the behaviour of both a fully HDV and fully AV, can arguably be derived from observing their performance in practice or in FOT, in the case of the fully AV (De Winter et al. 2014). However, behaviour of a partial AV (combined driver-ADCS control), whatever the level of automation, and of interaction between AVs and AV-AV is not readily available, due to the complexity of these interactions and vehicle control. A limited number of experiments have been performed on various areas, such as the driver-vehicle interaction (Saffarian et al. 2012), or potential AV-HDV interaction (Carsten et al. 2012; Saffarian et al. 2012), but still fail to give a generic, complete and acceptable understanding that can be readily applied in simulation.

In regard to driver-vehicle interaction, there has been much discussion on a driver's ability to perform interactive tasks together with an AV (Calvert et al. 2019b; Casner et al. 2016; Parasuraman et al. 2000; Poulter et al. 2008; Saffarian et al. 2012). There are principally two areas that are of direct relevance in this regard, namely the role of the driver in an AV; and the transition of control between vehicle and driver (Casner et al. 2016):

- (1) **The role of the driver** relates to a drivers ability to take on a new role that would require more monitoring and less operational actions, while still being able to trust and respond adequately to a system that they may not entirely comprehend. This throws up issues in regard to inattention, brittleness, trust, quality of feedback, and skill atrophy (Casner et al. 2016). Some have gone as far as to argue that a driver is not sufficiently able to perform the required tasks in an AV and should therefore not be subject to the subsequent threats (Axelsson 2017; Casner et al. 2016; Merat et al. 2014). There is an argument that can be made that a driver is not able to maintain meaningful human control under these circumstances (Calvert et al. 2019b). However, this remains a question to be answered by others, for which simulation can possibly aid the discussion.
- (2) **The transition of control** between driver and AV, in either direction, or also either voluntarily or mandatorily, is rightly also a hot topic of discussion (Zhang et al. 2017; Eriksson et al. 2017b). While voluntary control transition is often less of a problem as drivers make a conscious decision to retake control, mandatory transitions of control may come about at moments in which a driver is not sufficiently ready or able to retake control (Eriksson et al. 2017a; Merat et al. 2014), even if a properly designed automation system should avoid automation surprises, and facilitate proper trust on automation (Merat et al. 2012; Merat et al. 2009; Adell et al. 2008).

As the described issues are potential situations that will exist in practice, they should also be able to be modelled in simulation. Even if many uncertainties still exist, the current evidence together with realistic assumptions is sufficient to make initial estimations and certainly allow further methodological development. Assumptions made during this research will be substantiated, but also highlight the limitations to the current application, and also challenge the scientific community to further pursue increased evidence to calibrate and apply the model.

2.3 Summary of automated vehicle modelling

With the presence of significant challenges to further the state of the art in traffic simulation modelling, we summarise the main state of affairs and conditions identified to develop models able of considering many of the traffic dynamics that will be found in early automated driving amongst current conventional vehicles. Therefore considering that...

- Human driving behaviour is not 'robotic' and includes many stochastic effects related directly to cognitive processing,
- Most current simulation models are based on 'robotic' rules and most stochastics are often included exogenously, without describing the underlying driving mechanism,
- Automated vehicles drive, by definition, according to a set of rules and therefore resemble current simulation practice, limiting differentiation between AVs and conventional vehicles,
- Interaction between drivers of AVs with their vehicle (e.g. monitoring, transition of control), and with other AVs is not currently sufficiently captured in models,
- Human cognitive ability plays a significant role in driver behaviour,
- And, the interactive dynamics of AVs with each other and infrastructure is not yet properly understood.

Modelling of...

Conventional human driven vehicles should include:

- Real human driving dynamics
- Human reactions to automated vehicles

Partially automated vehicles should include:

- Reduced driver awareness when a driver is only monitoring
- Endogenous behavioural mechanisms to describe human reactions to transition of control (requests), including cognitive loading
- Consequence of interaction between driver and AV

Highly automated vehicles should include:

- AV driving dynamics and rules, for both longitudinal and lateral driving.
- Driving dynamics for interaction with other (automated) vehicles
- Additional driving dynamics for connected or cooperative driving

This list gives an initial overview of the main aspects we derive as important. The described framework in this contribution will be designed to accommodate them, but will not be able to explicitly address all of them due to a current lack of knowledge and data currently available on various points. By accommodating those not explicitly applied, allows them to be added later with relative ease. An example, is that of lateral driving of a fully automated vehicle, for which insufficient empirical evidence exists of how that may be performed in practice in the future.

3 Automated vehicles in a multi-level modelling simulation framework

In this section, we present the proposed extension of mixed AV-HDV traffic to an underlying multi-level modelling simulation framework.

3.1 Automated driving extension to modelling simulation framework

van Lint et al. (2018) proposed a multi-level modelling framework for microsimulation that explicitly includes human cognitive processes, on which the extension for automated vehicles is built. This framework models the driving task in a multi-layered fashion, with at the highest level, an ideal (in principle collision-free) base driving model for car following and other driving tasks. At the lowest level, state variables are defined that control how many tasks drivers execute and what the information processing load is of performed tasks, such as the driving task. These two layers are

connected by functions that are defined that govern the dynamics of high-level human factor parameters in the driver models with these state variables as inputs. The introduction of vehicle automation to the initial conceptual framework leads to the inclusion of elements that represent the Automated Driving Control System (ADCS) of a vehicle that may inherit some (low automation) or all of the driving tasks (high automation) from a human driver. The driving tasks are distributed between the driver and the ADCS, but also include connections between the ADCS and human driving, especially in the case of low or partial automated driving. A special case of interaction occurs when a transition of control (ToC) is carried out or at least when a take-over request (TOR) is made.

The extended conceptual framework with automation is depicted in Figure 1. The letters given in brackets are used to identify various parts of the framework from the Figure to the text and are used throughout the text. The human mechanisms from the original framework are still clearly present (indicated by a red background), but are now accompanied by the ADCS control (indicated by a blue background). The original framework contains the parts indicated by the letters (a)-(f), while the parts indicated by (m)-(p) as well as the ADCS Tasks, ADS Situational Awareness and the distribution of tasks have been added in the extended framework. Furthermore, the underlying mechanisms behind the flows (a)-(f) from the original framework have required adjusting to incorporate the driver interaction with automated driving and as detailed in the remainder of this section.

The main mechanisms are imparted to a reaction of the system using a functional equation that describes the collective effect of the human cognitive process in a driver model. Firstly, total task demands are computed for each considered (driving) task using (a) so-called fundamental diagrams of task demand and (b) task demand aggregation. Then the effect of those accumulated task demands is computed on (c) driver state and traits (desired speed, headway, etc.); on (d) situational awareness and as a consequence on (e) perception errors and (f) reaction time dynamics.

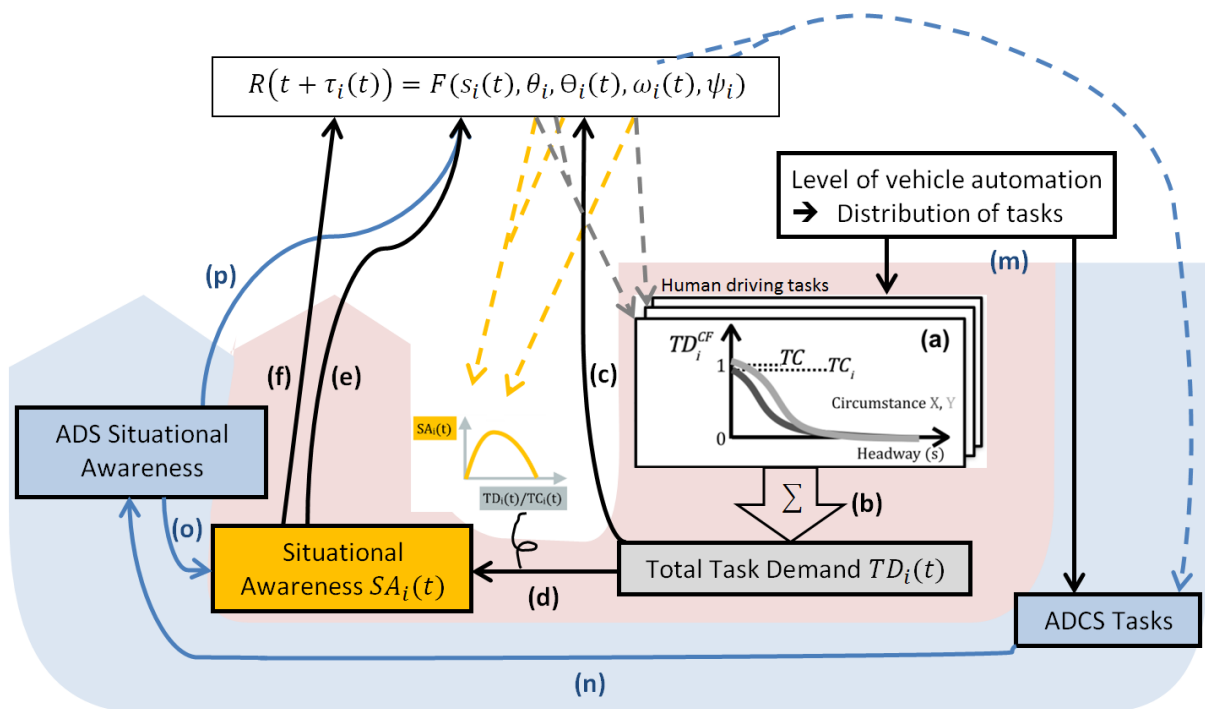


Figure 1: Conceptual framework for automated vehicle (blue is ADCS; red is human driver)

In an ADS, driving tasks are distributed over the human driver and the ADCS, depending on the level of automation and current driving state. Those tasks that are automated are passed to the ADCS (m) and are carried out based on the ADCS ability to perceive the environment, through its (perception) sensors (n). These sensors can also convey information to the human driver to assist their task (o),

for example through an in-car Human-Machine-Interface (HMI). And similarly to human driving, the ADCS perception may also include (small) errors and limitations (p), while physical reaction time is presumed to be negligible compared to humans, assuming perfect perception. A transition of control between human and ADCS driving is made at (m).

We will firstly revise on some of the main aspects of the framework and thereafter present the main parts regarding automated tasks in sections 3.2 and 3.3 and then focus on the inclusion of vehicle automation in 3.4 and 3.5 with explicit consideration of control transition in section 3.6.

3.2 Human task demand and task capacity (a) (b)

Each human has a certain task capacity TC at any one time, which allows them to undertake various tasks with varying levels of TD (Endsley 1995). When driving, the most important is the driving task, which can also be split into sub-tasks. There may also be secondary tasks that do not (directly) contribute to driving, but that may affect perception and response, for example in-vehicle or outside distractions. In simple terms, $TD(t)$ describes the cumulative workload of each cognitive task that a driver may be subjected to. The accumulation of all active tasks results in a person's total task demand ΣTD . These are summarized as follows:

TC	Nominal Task Capacity	Information processing capacity a nominal (standard) driver has available to execute tasks safely and efficiently. $TC = 1$ (or 100%).
$TC^i(t)$	Driver Task Capacity	Information processing capacity for driver i in units of TC
$TD_a^i(t)$	Driver Task Demand	Variable that describes how much information processing effort driver i requires performing a particular task a (safely and/or satisfactorily) in units of TC
$\Sigma TD^i(t)$	Total Driver Task demand	Sum of all task demands for driver i , that is,

$$TD^i(t) = \sum_a TD_a^i(t). \quad (1)$$

Although TD is shown in Equation 1 as a straight aggregation, in practice this will not be the case. However for simplicity this is assumed for the time being. The framework further assumes the relationship between TC and TD as a relative relationship, captured in the nominal variable Task Saturation TS :

$TS^i(t)$	Driver Task Saturation	Variable that expresses total driver task demand $TD^i(t)$ relative to $TC^i(t)$, that is,
-----------	------------------------	---

$$TS^i(t) = \frac{TD^i(t)}{TC^i(t)}. \quad (2)$$

In such a way, drivers with a task saturation $TS^i(t)$ close to (or larger than) 1 may experience deterioration in the performance level of tasks or may even be unable to perform certain tasks, as their task capacity has been exceeded. This performance deterioration may take the form of changes in awareness (larger perception errors, longer reaction times); changes in responses (smaller or larger sensitivities) and driver state (changes in other driver traits).

The level of TD is captured through the use of the so-called ‘‘Fundamental Diagram of Task Demand’’ (FDTD) van Lint et al. (2018). FDTD is defined as the functional relationship between a task depicted by a measurable variable, such as headway, speed, etc, and the cognitive demand that the task has on a driver as a function of the presumed variables. An example of such a FDTD is shown in Figure 2. It is obvious that many assumptions are required to come to such FDTD and that psychology can currently only give indications of relationships, rather than quantitative truths. Nevertheless, the concept of FDTD allows one to proceed with describing human behaviour in a tangible way by

making such plausible, even if not definitive, assumptions. Further details, argumentation and safeguards for the use of FDTD can be found in van Lint et al. (2018).

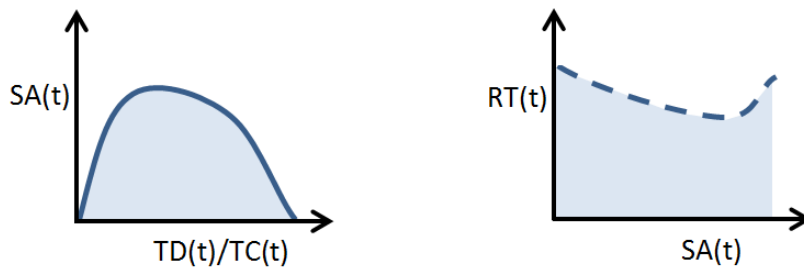


Figure 2: Fundamental Diagram of Task Demand (FDTD) and Reaction Time (RT) functions

3.3 Conceptual model for situational awareness (c) (d)

Following the cognitive demands placed on a driver through the TS , the influence on the ability of a driver in their situational awareness (SA) is considered. $SA(t)$ describes how well a driver is aware of their environment, particularly of those stimuli in the environment that a driver needs to safely and efficiently perform the driving task. The manner in which information is processed from perception through to the cognitive decision process is caught within the SA construct and depends on a driver's traits and current state, however this goes beyond the scope of the framework due to sufficient understanding of these processes. If a driver is 'oversaturated', then it is well known that their SA also suffers (De Winter et al. 2014). While high task saturation may reduce awareness, the same may also be true for very low task saturation (e.g. (Thiffault et al. 2003)), which is often described as inattention. This is also captured in the framework, as can be seen in Figure 2 by the concave function for $TS-SA$ at (d).

Following Endsley's dynamic situational awareness model (Endsley 1995; Wickens 2008b), three levels of SA are considered. These are (1) sensing the relevant objects and information; (2) comprehension (i.e. correctly interpreting this information); and (3) anticipation (making short term predictions for decision making). These three levels of awareness constitute three stages in the perception process. Like task demand, the SA variables may be chosen as continuous values (e.g. between 0 and 1), but one may equally argue for categorical, ordinal or fuzzy values (e.g. "bad", "moderate", "good"), or whatever parameterization works in a particular case. These three aspects affect driving performance in different ways and may also be (positively or negatively) influenced in different ways.

In the framework, both $TD(t)$ and $SA(t)$ are dynamic (i.e. they change over time and space); and they affect driving parameters (reaction time, frequency and magnitude of perception errors) and the response of drivers (sensitivities to e.g. distance gaps). A modelling choice can be made to simplify various connections or influences where limited empirical evidence is available or validity cannot be sufficiently given.

3.4 Driving tasks for automation (n) (p)

Contrary to human driving behaviour, an ADCS does not 'suffer' from high cognitive load and can process its tasks without exceeding a task capacity, presuming the computational power of the system is sufficient, which we assume it is. Therefore, all tasks are handled in the software with perfect performance according to their design (note that the design may not be perfect though). A similar story applies to the vehicle's perception sensors: these are designed to observe the environment objectively, and if we presume these are designed correctly, should be accurate (again, reality may be different in some cases). Theoretically, we therefore presume that the ADCS can

process tasks using its objective awareness of the direct environment without significant error. For Highly Automated Driving (HAD), this would lead to:

$$a_{HAD}^i(t + \tau^i(t)) = f(S^i(t), \theta^i(t), \omega^i(t)) \quad (3)$$

in which $a^i(t)$ denotes acceleration of the highly automated vehicle i ; $\tau^i(t)$ reaction time, which approaches 0; $S^i(t)$ a set of available stimuli e.g. speeds, speed differences, distance gaps with respect to the ego-vehicle i and its leader(s); while θ^i is a set of driver or ADACS preferences (e.g. car following parameters), which are still required in an ADACS, and may be selected by the driver or hard-coded in the ADACS. The sensitivity term to these stimuli; $\omega^i(t)$, does still exist in an ADACS, however is programmed within the ADACS software according to prescribed rules. From this, it is clear that similar elements do exist between HAD-ADACS and human driving, such as headway and speed preferences, but with the main difference being in the static mechanics that govern that ADACS and make its performance rigid, but consistent.

While the ADACS performs some or all driving tasks, a driver remains present and with a certain level of cognitive ability and driving performance. This is especially relevant for low level automation where the driver still has tasks to perform or partial automation where a driver may need to retake control. Under these conditions, the equations and mechanism, as described in Equations 1-3, still hold for the human driver. Low level automation will require a sharing of tasks, as some elements of driving are controlled by the ADACS and some by the human driver. This requires a human driver to have a certain understanding of how the ADACS works, as separated tasks will influence each other. For example, human steering is affected by the automated longitudinal control (e.g. with ACC) and must align with the longitudinal movement. This can lead to an increase in TD for the lateral task (steering), while the longitudinal task may decrease (note: not disappear, as monitoring is required). It is conceivable that a reduction in the total task demand of a driver, may result in their SA dropping due to inattention (Zeeb et al. 2015; Young et al. 2013). This process is captured in the concave shape of the FDTD (see Figure 2a), which would lead to a reduced performance in driving. For tasks that would become monitoring tasks for a human driver, a time- and traffic state dependant TD reduction factor η_i may be applicable:

$$TD_{monitoring}^i(t) = \eta^i(t, \omega^i(t), \theta^i(t)) \cdot TD^i(t) \quad (4)$$

As well as η^i being dependant on time and the characteristics of the (traffic) environment ω^i , it would also depend on the level of automation and a drivers own skills and experience θ^i . A higher level of automation would require less effort from a driver and would result in a higher task demand reduction, therefore a lower factor value of η^i , just as a more experienced and skilled driver may also lead to lower η^i value.

3.5 Driver reaction and model (e) (f)

As a consequence of the influence of SA and of a drivers TS on their driver state and of course of the surrounding environment (i.e. location, speed, etc of other vehicles and infrastructure), the response of a driver is determined for that time instance. The response R , given as a function of these variables and shown in Figure 1, indicates the effect that the environment and the driver behaviour has on the dynamics of their vehicle. While in manual driving mode, these dynamics come directly from the driver's decisions and actions. For automated driving, the influence will depend on the driver's role at any given time.

The response is given by the acceleration of the vehicle, as is common in most simulation models. Therefore, the response function is written as:

$$a^i(t + \tau^i(t)) = f(S^i(t), \theta^i(t), \omega^i(t)) \quad (5)$$

in which $a^i(t)$ denotes acceleration; $\tau^i(t)$ reaction time; $S_i(t)$ a set of available stimuli (such as speeds, speed differences, distance gaps) with respect to the ego-vehicle i and its leader(s); θ^i a set of driver preferences (e.g. car following parameters); $\omega^i(t)$ is a set of characteristics of the (perceivable) world $PW^i(t)$ for driver i that may affect the response (e.g. control, visibility, etc.). In these variables, the subscript i denotes driver (i) specificity, and t denotes (continuous) time.

3.6 Transition of control (m)

Arguably, one of the most relevant and important interactions between human and ADCS driving is when control transitions from the one to the other: Transition of Control (ToC). From a human driver's perspective, this involves a change in tasks and TD, while a vehicle is moving and is therefore a potentially critical procedure. The focus here is on a transition from ADCS to human, which may be voluntary and planned by the human driver, or may be initiated by the ADCS and could be immediate or with a required Take-over time. Increasing amounts of research have been performed on ToC in automated vehicles, such that good insights exist into the physical (reaction-time and performance) and cognitive (task demand and workload) effects of a control transition (Varotto et al. 2018). Based on findings from literature (Eriksson et al. 2017b; Zeeb et al. 2015; Merat et al. 2014; De Winter et al. 2014; Lu et al. 2015; Varotto et al. 2018), we have constructed a hypothesis for the mechanism of ToC within the proposed framework, which is shown in Figure 3 and described thereafter.

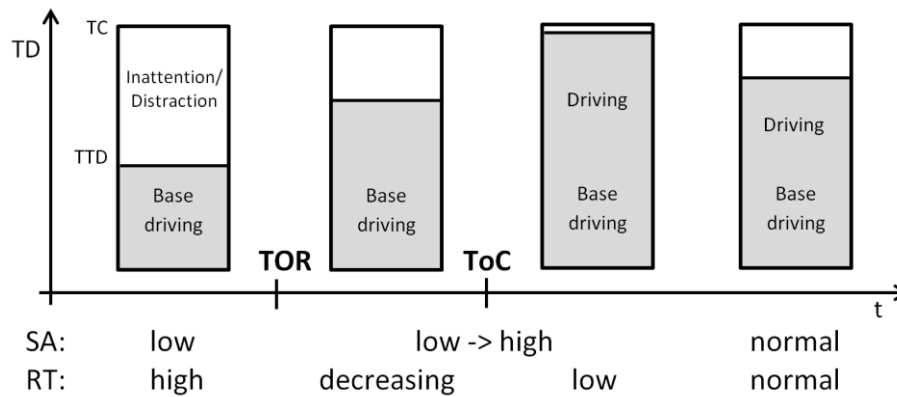


Figure 3: Transition of Total Task Demand (TTD), Situational Awareness (SA) and Reaction Time (RT) during a Transition of Control (ToC)

Prior to a Take-Over Request (TOR), drivers are often shown to be inattentive or distracted to some degree (Louw et al. 2015; Merat et al. 2014), which has a detrimental effect on their situational awareness (SA) (Eriksson et al. 2017b; Zeeb et al. 2015; Merat et al. 2009; Stanton et al. 2005) and reaction time (RT) (Eriksson et al. 2017b; Merat et al. 2014). At the point that a TOR is made (or the necessity arises that a driver initiates one), an increase in the total task demand (TTD) occurs, due to a new additional task. The TTD rises to near or, in some cases, above the task capacity (TC) (Eriksson et al. 2017b; De Winter et al. 2014). At the point of ToC, a driver may be more alert and have had time to refocus their attention to the driving task (Zeeb et al. 2015; Merat et al. 2014). The extent of this and required time depends on the Take-over time, the level of potential driver distraction/inattention and personal traits and state, among other things (Zhang et al. 2017; Eriksson et al. 2017b). This will see an increase in SA and a decrease in RT. Once, the control transition is complete and normal driving has resumed, a driver's TTD will return to normal levels, as well as their SA and RT (Merat et al. 2014). This description is purposely generic to allow it to be implemented in the framework for a proof of concept. We are well aware that there are a great number of deviations to this process and that these mechanisms can work differently, under different circumstances.

The relationship between the TTD and SA is captured within a concave formulation of the FDTD. The RT is expected to be inverse-proportional to SA as long as the $TTD < TC$, and may increase again

slightly when the task demand is saturated to a decreased inability to perform each task to the highest level. These functions are illustrated in Figure 2 **Error! Reference source not found.**

4 Simulation case experiment

4.1 Case descriptions and scenarios

Two experimental cases are chosen that allow us to demonstrate the general validity of our approach against qualitative evidence found in literature in regard to human reactions to Transition of Control (ToC). There are many empirical experiments that consider the take-over time (many summarized in Eriksson et al. (2017b) among others), however there are limited experiments that target *and* quantify the effect on Workload and Situational Awareness to an extent that we can apply it in a case here (note: there are experiments that do consider Workload (WL) and Situational Awareness (SA), but the results are not or insufficiently quantifiable for simulation validation). One experiment and analysis that does consider human reaction time offset versus an indicator of SA is that performed by Zeeb et al. (2015), which we use for our case and validation. The case experiment description given below is based on the one that can be found in Zeeb et al. (2015), in which three different types of drivers were considered: high-, medium- and low-risk drivers, as defined by the frequency that a driver performed off-road glances and is used as an indicator of their SA (Zeeb et al. 2015; Konstantopoulos et al. 2010; Underwood 2007). For example, a high-risk driver performs relatively more off-road glances, which indicates a lower SA.

In the experiment, we consider the following two cases:

1. An emergency Take-over request (TOR) for a single vehicle, with varying driver traits and states
2. Multiple TOR's for different automated vehicles at the same location

The first case allows the framework to be validated against empirical data, while the second case gives a demonstration of the framework for a broader, more generic situation.

4.1.1 Case 1: Emergency take-over request

The first set of scenarios aligns to the experiments analysed by Zeeb et al. (2015). A two-lane freeway corridor is considered with free flowing traffic and a speed limit of 120 km/h. Traffic demand is a uniform 900, 1200 or 1500 veh/hr. An ego AV, with automated lateral and longitudinal control aligned to a SAE level 2 vehicle, driving on the slow lane is in car-following mode behind another vehicle. The leading vehicle is large enough to restrict the ego vehicle and driver's vision beyond the leading vehicle. At a certain moment in time, the leading vehicle performs an emergency braking manoeuvre for an arbitrary reason. Within 1 second of coming to a full standstill, the leading vehicle starts to move again. The ego vehicle, following at a gap of 2.5-3.5 seconds, transitions to the human driver with a delay that corresponds to the driver's level of SA. The human driver does not have the opportunity to perform a steering manoeuvre due to a convoy of several vehicles in the fast lane and the absence of a hard-shoulder, and therefore can only perform an emergency braking manoeuvre to avoid a collision. As the experiment is setup such that lane-changing and lateral avoidance is not required, the application in the model with a single lane road and without lane-change model suffices. Different scenarios are carried out for different driver characteristics, which are aligned to the high-, medium- and low-risk drivers, as described (Zeeb et al. 2015) relating to their level of awareness. The corresponding characteristics are given in Section 4.2 and the experimental situation is depicted in Figure 4.

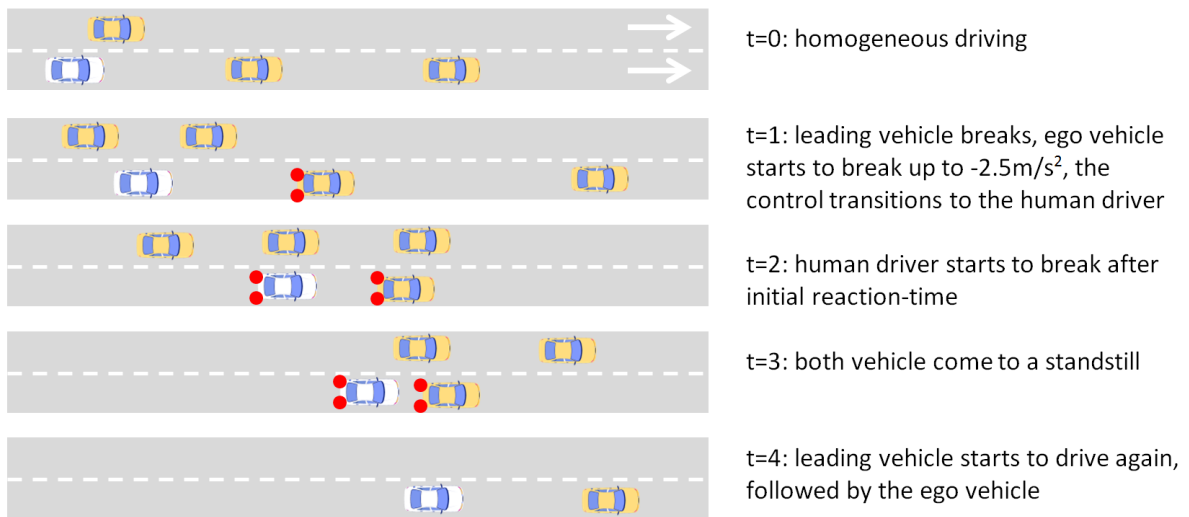


Figure 4: Case 1 emergency braking, graphical overview; white vehicle is the ego-AV

4.1.2 Case 2: Location triggered take-over request

The second case considers the same freeway corridor as the first case, however with a greater traffic flow of 2200 veh/hr. The traffic composition exists of a mix of partially automated and manual driven vehicles. The AVs are assumed to be SAE level 2 vehicles, with both lateral and longitudinal automated control. The position of the AVs in the traffic is random. At a certain location along the corridor, a TOR is made by the automated vehicles. The location of this request is identical for all AVs, and can be presumed to be triggered by an infrastructural characteristic, such as missing lane markings on a short stretch of road. The TOR is made immediately upon the vehicles reaching the location with control immediately transferred to the human driver. Six different scenarios are defined based on the penetration of AVs of 10%, 20%, 40%, 60%, 80% and 100%. The different levels of penetration allow us to show what the potential traffic flow effect could be as a consequence of a mandatory ToC for multiple vehicles and judge the face validity thereof. The experimental setup is shown in Figure 5.

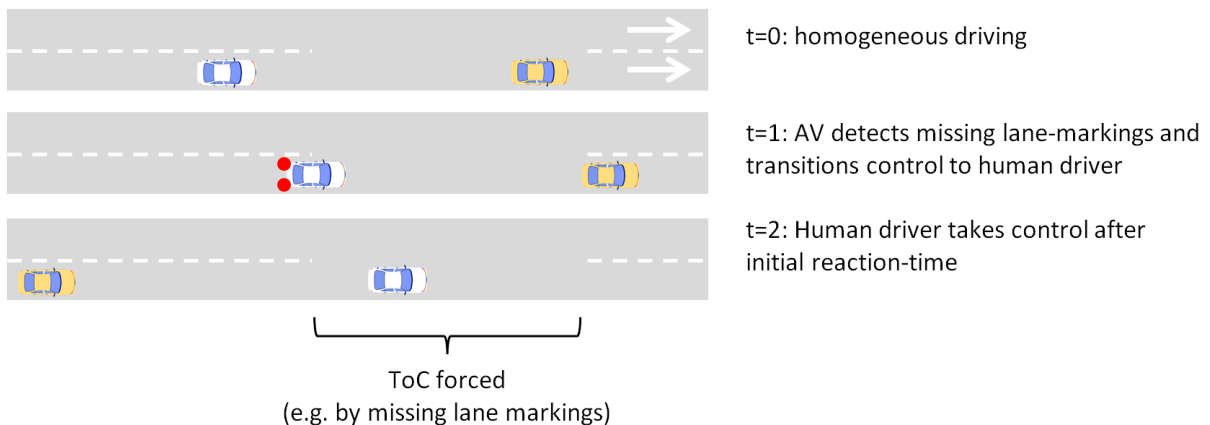


Figure 5: Case 2 missing lane-markings, graphical overview; white vehicle is the ego-AV

4.2 Applied traffic model and automated vehicle dynamics

The described cases are applied to the framework, which contains a traffic simulation model that performs the vehicle spatiotemporal time-stepping and also contains descriptions of human factors and further automated vehicle characteristics. The manner in which each of these elements is applied in the framework for the scenarios is described here.

The basis for vehicle movement is initiated through the applied traffic simulation model, which is later influenced by the applied human factors and described in Section 4.3. The base model that we use is the Intelligent Driver Model plus (IDM+) (Schakel et al. 2012), which is a car-following model based on the original IDM by Treiber et al. (2000). The main difference with the IDM is a separation of the free and car-following terms. The car-following acceleration is determined for a vehicle i using Equations 6 and 7:

$$a^i(t + \tau_i) = a_{max}^i \min \left(1 - \left(\frac{v^i(t)}{v_0^i(t)} \right)^\delta, 1 - \left(\frac{s^i(t)}{s_i^*(t)} \right)^2 \right) \quad (6)$$

$$s_i^*(t) = s_0^i + v^i(t) \cdot T^i(t) + \frac{v^i(t) \cdot \Delta v^i(t)}{2 \sqrt{a_{max}^i b_{comf}^i}} \quad (7)$$

Here, the parameter a_{max}^i is the maximum acceleration, b_{comf}^i is the maximum comfortable deceleration, v_0^i is the desired speed, T^i the desired time-gap and s_0^i is the stopping distance. Furthermore we have speed $v^i(t)$, speed difference $\Delta v^i(t)$ and headway with the leader s . Finally, for parameter δ we use a standard value of 4, which reduces the maximum acceleration as speed increases. For the base case we apply the following values: $\tau^i = 0$; $a_{max}^i = 3\text{m/s}^2$; $b_{comf}^i = 3\text{m/s}^2$; $v_0^i = 35\text{m/s}$; $s_0^i = 8\text{m}$ and $T^i = 1.2\text{s}$. As the considered cases only require longitudinal modelling of vehicles, the applied model does not need to contain a lane-changing component and the use of only a car following model suffices.

The vehicle dynamics for AVs in the simulation are presumed to be identical to the basic control dynamics that follow from the IDM+ as given here. Human drivers on the other hand display both a greater randomness in their operational control of vehicle (Kuderer et al. 2015; Lefèvre et al. 2015) as well as being cognitively affected in their ‘emotional’ behavior, as has already been highlighted in this paper. The influence of the cognitive influence on behavior is included through the elements of a driver’s mental workload and situational awareness as described in Section 3. These elements have an influence on a driver’s immediate desired speed v_0^i and their desired time-gap T^i for each time step in the simulation model. A further influence on a human driver’s vehicle movement follows from their perception of the environment, which contains errors. This means that for each time step a subjective value for the speed $v^i(t)$, speed difference $\Delta v^i(t)$ and headway with the leader s , may be used that can deviate from the objective values due to an error in perception. Finally, a driver’s reaction time τ^i may also be affected by their current state. The manner in which the driver’s cognitive processing of their human factors in relation to their driving performance is explained in the following sub-section.

4.3 Human factors setup

For the application of the influence of human factors in the experiment, we have made a number of assumptions. These assumptions are made such that proven or plausible relationships between human driving behaviour and performance are considered, while not overcomplicating their application in areas for which only constructs rather than quantitative connections exist. As the goal of the experimental case is to demonstrate the framework, we will leave the investigation of detailed driving tasks for another paper.

4.3.1 Driver tasks and task demand

In this experiment, we consider a driver to be affected by two task demands: the driving task, and a potential ToC task. The driving task demand follows from all processes that involve longitudinal driving of a vehicle. As we only consider car-following (CF), we will refer to this task demand as TD_{CF}^i for a driver i . Similarly to other literature (van Lint et al. 2018), we make a simplified assumption of how the TD_{CF}^i is affected by a drivers environment and perception. We assume that a driver has a

higher TD_{CF}^i in denser traffic, in which they follow a leader at a smaller time headway, while a larger gap places less TD_{CF}^i on a driver. This very simple assumption also holds with Fullers description of risk and risk limitation (Fuller 2011). The assumed function is a four part piecewise function that considers: critical, regular, safe, and non-car-following parts, defined as the time headway from the ego vehicle to their leader: h_0^i . The function is shown in Figure 6a and is given by:

$$TD_{CF}^i(h) = c_{CF} \cdot \begin{cases} TD_{max,CF}^i - \frac{h - h_{crit}^i}{h_{max}^i(a) - h_{crit}^i} (TD_{max,CF}^i - TD_{crit,CF}^i) & h \leq h_{crit}^i(a) \\ TD_{crit,CF}^i - \frac{h - h_a^i}{h_{crit}^i(a) - h_a^i} (TD_{crit,CF}^i - TD_{a,CF}^i) & h_{crit}^i(a) < h \leq h_a^i \\ TD_{a,CF}^i - \frac{h - h_b^i}{h_a^i(a) - h_b^i} (TD_{a,CF}^i - TD_{b,CF}^i) & h_a^i(a) < h \leq h_b^i \\ TD_{b,CF}^i & h > h_b^i \end{cases} \quad (8)$$

Where, $TD_{max,CF}^i$ is the maximum level of task demand for car-following, $TD_{crit,CF}^i$ the CF task demand at a critical time-headway $h_{crit}^i = 0.6s$, $TD_{a,CF}^i$ the CF task demand at $h_a^i = 2.0s$, and $TD_{b,CF}^i$ the lowest CF task demand above $h_b^i = 4.0s$. $\{TD_{max,CF}^i, TD_{crit,CF}^i, TD_{a,CF}^i, TD_{b,CF}^i\}$ are set at $\{1.0; 0.8; 0.6; 0.4\}$. The constant c_{CF} is a reduction factor for the CF task demand for levels of automation, as the CF task operations will demand less from a driver depending on the SAE level. Arbitrary values are applied for low (SAE1-2), partial (SAE3) and high (SAE4-5) automation of $c_{CF} = \{0.85; 0.5; 0.25\}$.

For the ToC task demand TD_{ToC}^i , we again make use of (arbitrary) assumptions in regard to the cognitive process based on indications of the process from literature (de Waard et al. 2008; Liu et al. 2006; Wickens 2008a; Wong et al. 2009). This is described as a linearly descending function as a function of the time that has elapsed since a TOR. Upon a TOR occurring, the TD_{ToC}^i is immediately activated and has a high level of demand, which is due to an initial processing of the request being made to a driver. As the driver becomes increasingly aware and 'tuned-into' which actions they need to perform, the level of TD_{ToC}^i then decreases. After the ToC has taken place at t_{ToC} , a driver's TD_{ToC}^i may still be present as they are still adjusting to the driving task after retaking control. After a certain time T_{ToC} , the TD_{ToC}^i will diminish completely. In the case here, the $t_{TR} = t_{ToC}$. The shape of the function is shown in Figure 6b and given by:

$$TD_{ToC}^i(t) = TD_{max.ToC}^i \cdot \frac{t_{ToC} + T_{ToC} - t}{T_{ToC}} \quad \text{where } t = [t_{ToC}; t_{ToC} + T_{ToC}] \quad (9)$$

Here, the $TD_{max.ToC}^i$ is the maximum ToC value of the task demand, which is set at 1.2. A value above 1.0 indicates that a task demands more from a driver than they can give, which we assume is the case immediately after an unexpected TOR is made. t_{ToC} is the time that the ToC is made, while T_{ToC} is the duration of the ToC task.

As part of the task demand, we also deliberated on including an inattention task that may be present while a driver is not in operational control before a TOR, as there is plentiful evidence that inattention plays a role (Louw et al. 2015; Young et al. 2013). However, we opted against this due to a lack of clarity and necessity on how it would influence a driver's total task demand at and after the point of a TOR and ToC. In essence, the function chosen for the TD_{ToC}^i inadvertently captures a possible consequence of inattention with a high initial value for TD_{ToC}^i . Therefore inattention is not explicitly considered in this experiment.

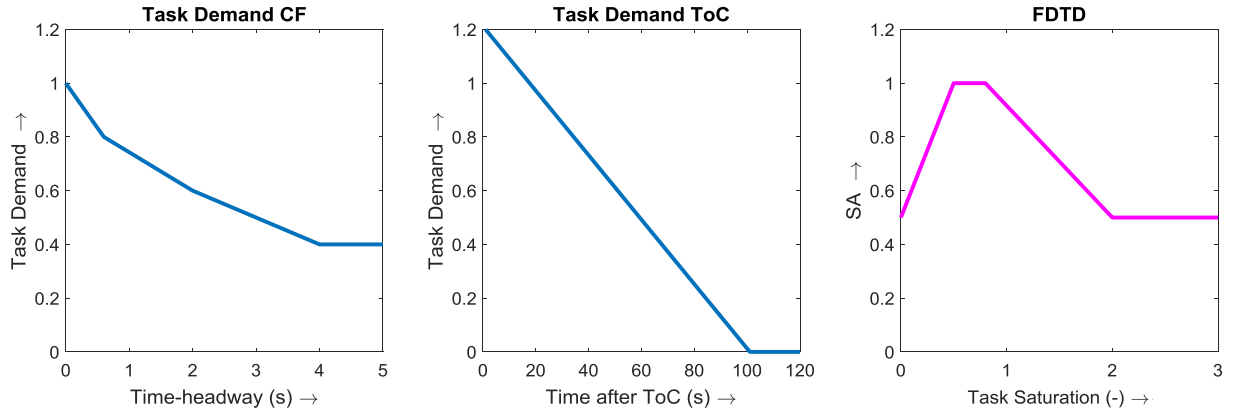


Figure 6: Applied piecewise functions for: TD car-following, TD ToC, and FDTD

4.3.2 Driver workload and awareness

The approach applied for driver workload through TD and SA makes use of the FDTD and has been explained in Section 3 of this contribution and was introduced in van Lint et al. (2018). The FDTD specifies the relationship between the task saturation (TS) on a driver and their SA. The TS is basically the total aggregated task demand in regard to a static task capacity: $TS^i(t) = \sum_k TD_k^i(t)/TC^i(t)$. A piece-wise representation of the concave form of the function, shown in Figure 3, is given. Therein, a low TS_{inatt}^i results in a lower SA^i due to potential inattention, while $TS^i(t) > TS_{crit}^i$, will result in a lower SA^i . The function is given by:

$$SA(TS(t), t)^i = \begin{cases} SA_{max}^i - \frac{TS^i - TS_{min}^i}{TS_{inatt}^i - TS_{min}^i} (SA_{inatt}^i - SA_{max}^i) & TS^i < TS_{inatt}^i \\ SA_{max}^i & TS_{inatt}^i \leq TS^i < TS_{crit}^i \\ SA_{max}^i - \frac{TS^i - TS_{crit}^i}{TS_{max}^i - TS_{crit}^i} (SA_{max}^i - SA_{min}^i) & TS_{crit}^i \leq TS^i < TS_{max}^i \\ SA_{min}^i & ts \geq TS_{max}^i \end{cases} \quad (10)$$

The time notation (t) has been omitted from Equation 10. Furthermore, TS_m^i with $m = \{min; inatt; crit; max\} = \{0; 0.5; 0.8; 2.0\}$ and SA_n^i with $n = \{min; inatt; max\} = \{0.5; 0.5; 1.0\}$. The applied parameters values, are selected here to allow the framework to produce the desired behavior that is expected.

4.3.3 Effect on human driving performance

The influence of drivers' human factors, as described in the previous paragraphs, affect the quality of their perception of the environment, thus leading to (small) errors, and affects the RT of their actions. Both of these processes are easy to understand and are backed up by the previously cited literature. The assumption is that reduced awareness exacerbates known perception biases, that is, either an under- or overestimation of both distance gaps and (relative) speeds (Lee et al. 2017; Nilsson 2000).

Perception errors are included in the framework through applying a perceived speed difference $\Delta v_{perceived}^i$ and gap $s_{perceived}^i$ from the ego vehicle to a leader. The perceived values, which are what the driver 'experiences', are a function of the objective speed difference $\Delta v^i(t)$ and gap $s^i(t)$ and of a divers SA at time t , and are as also applied in van Lint et al. (2018):

$$s_{perceived}^i(t) = (1 + \delta^i \epsilon_{SA}^i(t)) s^i(t) \quad (11)$$

$$\Delta v_{perceived}^i(t) = (1 + \delta^i \epsilon_{SA}^i(t)) \Delta v^i(t) \quad (12)$$

in which $\epsilon_{SA}^i(t)$ is the error term for reduced SA, the difference between optimal SA and actual SA, on perception and is defined as

$$\epsilon_{SA}^i(t) = SA_{max}^i - SA^i(t) \quad (13)$$

δ^i is a term that indicates if there is an over ($\delta^i = 1$) or under ($\delta^i = -1$) estimation in perception. In this experiment, we assume that perceived differences are smaller than the objective differences, therefore applying $\delta^i = -1$.

The RT of a driver i is included in the model through the $\tau_i(t)$ term found in Equation 13. The extent of $\tau_{SA}^i(t)$, which is additional reaction time caused by suboptimal SA at any time t , is a function of a driver's SA error:

$$\tau_{SA}^i(t) = \epsilon_{SA}^i(t) \tau_{SA,max}^i \quad (14)$$

With the total RT being the sum of this additional reaction time and the physical reaction time, which represents the lag from the moment a driver makes a decision until an action starts taking effect on a vehicle:

$$\tau^i(t) = \epsilon_{SA}^i(t) \tau_{SA,max}^i + \tau_p^i \quad (15)$$

In this experiment, the maximum SA reaction value $\tau_{SA,max}^i = 1.4$, while we presume the physical lag time $\tau_p^i = 0.6$ for manual driven vehicles and $\tau_p^i = 0.1$ for automated controlled vehicles. More details on this approach to reaction time can be found in van Lint et al. (2018).

In such a way, the effects of driver tasks, including ToC, are endogenously applied to driving performance through a driver's WL from the tasks and SA.

4.4 Performance indicators

The cases and their scenarios are evaluated using two levels of analysis. The first pertains to the global effects on traffic flow to give an indication of the general qualitative effect on traffic in a scenario. This is shown by means of trajectory plots of vehicles in a time-space diagram, which show the influence on speeds and interactions between vehicles throughout the considered experimental corridor and allow face validity check.

The second level of analysis is quantitative and focusses on the time-specific effects of the scenario on pre-selected driver-vehicle combinations in regard to traffic variables and human factor variables. The ego-vehicle in each case and a significant other vehicle are considered. The time-profile of the driver TD, SA, vehicle speed, vehicle acceleration, driver RT and the time to collision (TTC) are all displayed. The considered RT is the reaction time required in the cognitive process and is therefore the net RT, which does not include the physical delay in carrying out an action, such as pressing a pedal, engine delay, etc. Therefore, the net RT's that will be found are lower than the often considered gross RT, which consider the observable time until response. This is by choice, as we are explicitly considering the cognitive process and does not influence the general demonstration of the framework. The TTC is defined as the duration of time taken at an instant moment in time before a following vehicle would collide with a leading vehicle under the assumption that both vehicles current speeds remain constant:

$$TTC^i(t) = \frac{s^i(t)}{\Delta v^i(t)}, \Delta v^i(t) > 0 \quad (16)$$

TTC is commonly applied as a safety indicator, although it should be noted that it is usually only affective in circumstances with fast changing vehicle speeds and does not consider vehicle proximity independently. In case 2, the travel time profiles as a function of departure time over the corridor is applied as an additional a quantitative macroscopic indicator.

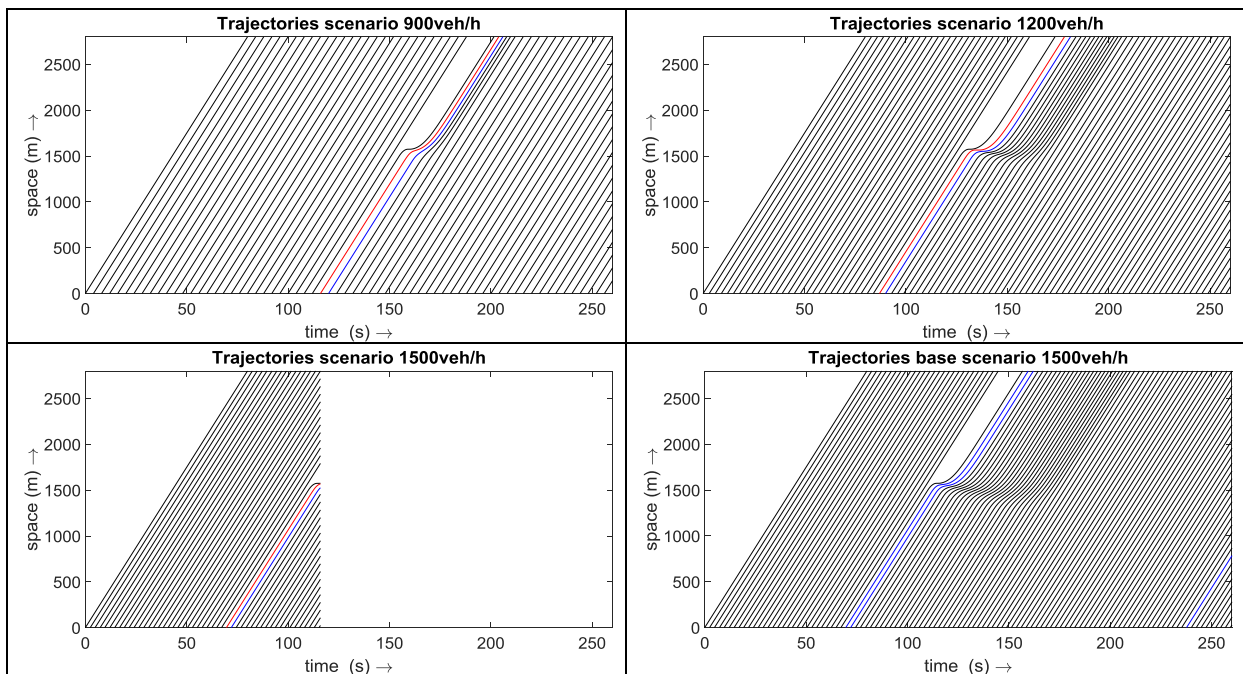
Finally, the framework was implemented as a custom built model in MATLAB. As such a framework does not exist yet, it was not possible to easily use an existing modelling suite. The use of MATLAB allowed us to implement the framework in a modular based approach, closely following the scheme shown in Figure 1.

5 Results

The results from the experiments, as described in Section 4, are given in this section and are further discussed in Section 6. We start with the first case that considers the effect of a Transition of Control (ToC) due to an emergency braking manoeuvre ahead of the AV. In Section 5.2, we show the results from the second case, in which multiple ToC's are performed in traffic at an identical location. This shows the broader effects under different degrees of AV penetration is a location-bound ToC is made using the framework.

5.1 Case 1: Emergency transition of control

In the case where a ToC is required for an emergency procedure, we test three different levels of traffic flow, namely a uniform traffic demand of 900, 1200 and 1500 vehicles per hour per lane. This corresponds to a time-headway between vehicles of 4.0, 3.0 and 2.4 sec, assuming the vehicles are driving at the set speed of 35 m/s. The trajectory plots of the three scenarios and of the reference scenario, in which all vehicles are manually driven in traffic flow of 1500 veh/hr/lane, are shown in Figure 7a-d. The AV (shown in red in Figure 7) is situated directly behind the vehicle that performs the emergency stop (shown in blue in Figure 7).



**Figure 7: Case 1 vehicle trajectories with different traffic demand;
Top-left to bottom-right: a) 900veh/h, b) 1200veh/h, c) 1500veh/h, d) reference 1500veh/h**

From the trajectory plots, a number of things are immediately obvious. In the 900 and 1200 veh/hr demand scenarios (Figure 7a-b), the driver of the AV is able to decelerate in time to avoid a collision with the leading vehicle. For the 1200 scenario, this causes a slightly greater disturbance in the traffic flow behind the vehicle than for the 900 case due to the small time headways between the vehicles. In the case of the 1500 scenario (Figure 7c), the driver of the AV is not able to assume control and decelerate on time and collides with the leading vehicle, at which time the simulation ceases as designed. We will zoom in on the process that precluded the collision event when we review the vehicle and HF variables here below. In the reference scenario (Figure 7d), for which no ToC is required, we see that the driver is able to perform the emergency braking manoeuvre in time to avoid colliding with the leading vehicle.

We now explore the underlying processes of the drivers and vehicles leading up to the above events. To do this, we review the Human Factors (HF) through the Task Demands (TD) and Situational Awareness (SA); The vehicle dynamics through the vehicles speed and acceleration; And finally the interaction through the drivers reaction time and Time-to-Collision (TTC). The two vehicles following the braking leader are considered. The immediate following vehicle (veh 30), the ego vehicle, is the AV for which a ToC is required. The next following vehicle (veh 31) is a manual non-automated vehicle and is used for comparison with the AV. The results are shown in Figures 9-12 for each scenario and are discussed in order.

First we consider the 900 scenario. Upon the leading vehicle braking, we see an initial braking manoeuvre (Figure 8c) performed by the AV after which the AV transitions control to the human driver due to the system reaching a critical level of required deceleration. The TD of the driver during automated control is not relevant due to the absence of a driving task. At the point the TR is made, the drivers TD_{tot} peaks due to the accumulation of the driving task and the ToC task (see Figure 8a), as described in Section 4.3. After a short time, in line with the function defined and shown in Figure 6, the TD_{tot} starts to decline as the TD_{ToC} decreases and the driver becomes more aware. The increase in awareness is shown in Figure 8a by the dashed line and is initially is low, but starts to increase as the TD_{tot} returns to a lower value. The response of the drivers low SA initially results in a higher RT (Figure 8d). As a consequence, an emergency braking manoeuvre is delayed (Figure 8c) and the TTC reaches a critical value (Figure 8d) of 1.8 sec. The manually driven vehicle (veh 31) by comparison shows a different HF process. Initially, the TD_{tot} is below 0.5 and the SA is below 1.0, as the driver maintains a relatively long time headway of 4.0 sec. Upon the leader braking hard, the time-headway decreases, but remains above a critical level. The TD_{tot} increases slightly, leading to a higher SA and marginally shorter RT (Figure 8e). As a consequence, vehicle 31 is able to reduce speed much quicker and only experiences a critical TTC of 3.4 sec.

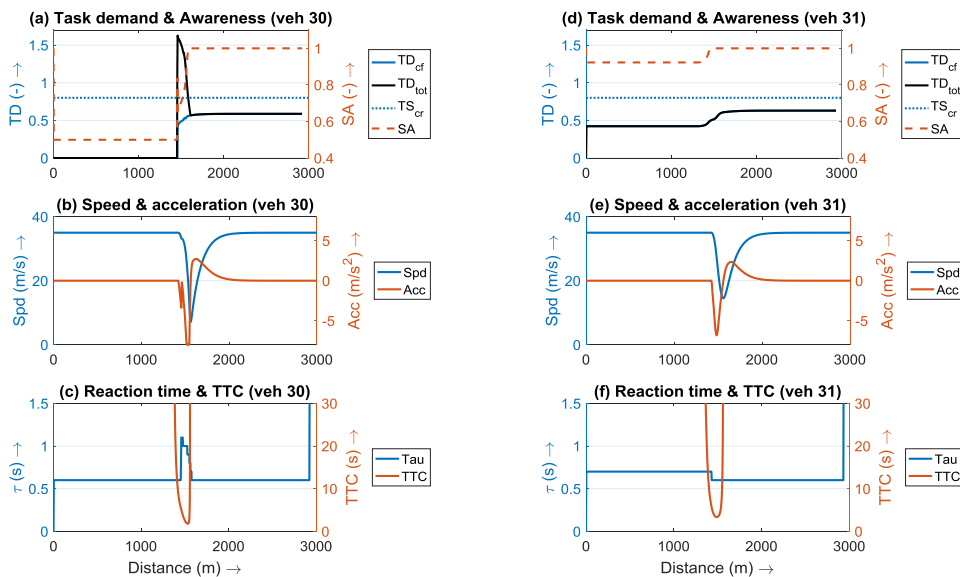


Figure 8: Vehicle and human factor variables - 900veh/h scenario

The 1200veh/hr scenario shows a generally similar pattern to that of the 900 scenario. As traffic is busier and the time headways shorter, we see that the TTC of the AV and manual vehicle are lower at their critical points (Figure 9c+f) due to the reaction times of drivers with TTC-values of 0.9 and 1.7 seconds respectively. As the time-headways are shorter, the TD for the human driver is also higher compared to the 900 scenario, which also translates to a higher initial SA.

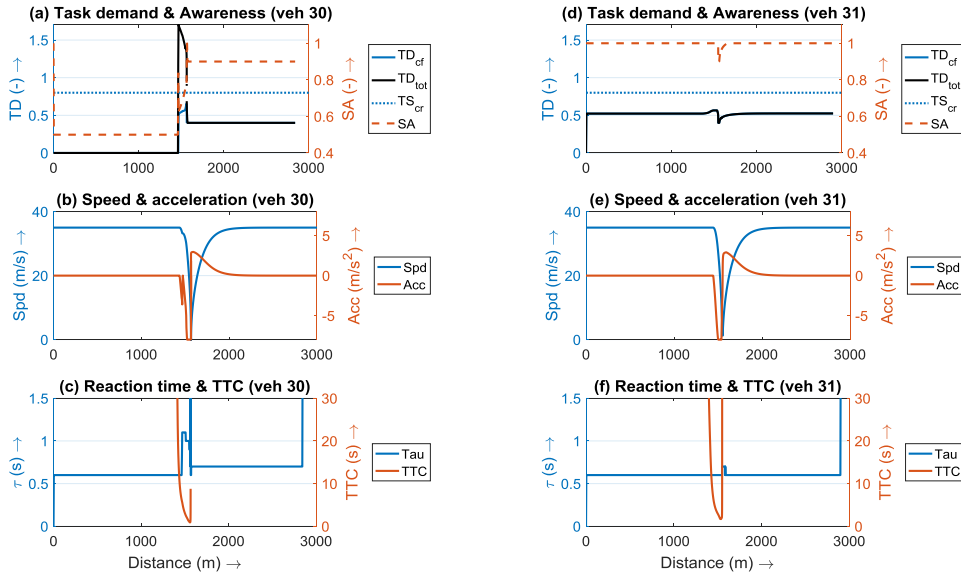


Figure 9: Vehicle and human factor variables - 1200veh/h scenario

In the 1500 scenario, the 2.4 sec time-headway is no longer sufficient for the AV after a ToC to decelerate in time and avoid a collision. The mechanism leading up to the collision is very similar to that of the 900 scenario that is described above. The driver upon ToC has an initially high TD_{ToC} due to the CF task and the ToC task, which results in a lower SA and higher RT. The consequence of the RT together with the lower time headway did not give the driver of the AV sufficient time to decelerate as resulted in a negative TTC (see Figure 8a-c).

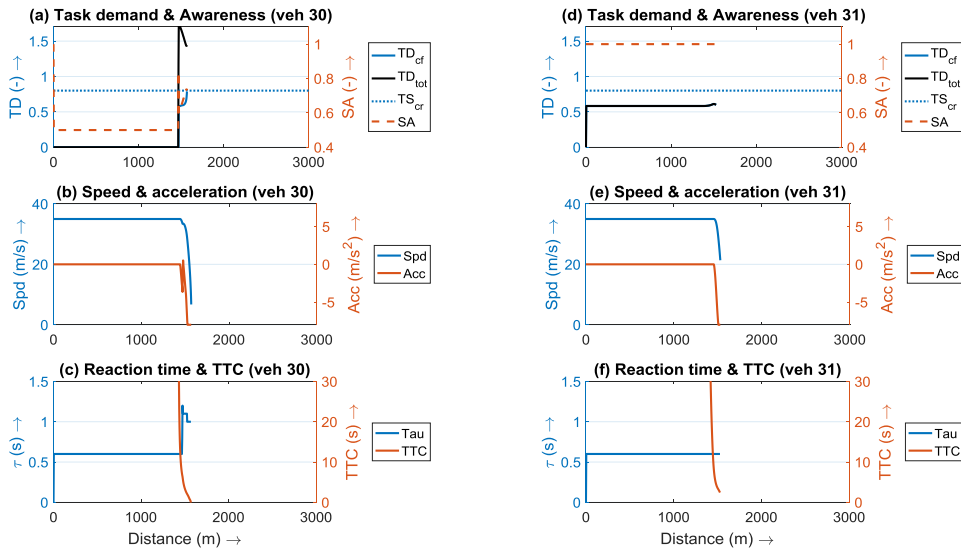


Figure 10: Vehicle and human factor variables - 1500veh/h scenario

A comparison is made with the 1500 scenario and the reference scenario (also 1500 veh/hr), in which all vehicles are manually driven, to show the difference in outcome and the effect that the ToC has on the driver and AV. Prior to the braking event, the manual driver has a steady TD_{ToC} of 0.6 and a high level of SA, due to the proximity of a leading vehicle. The braking manoeuvre causes an initial increase in TD_{ToC} followed by a short decrease, which follows the hard braking by the leader and initially a short time-headway and then a higher headway as both vehicles decelerate to a low speed. The TTC drops to a critical level of 1.5 seconds and once the leading vehicle starts to move again, all variables return to stable values.

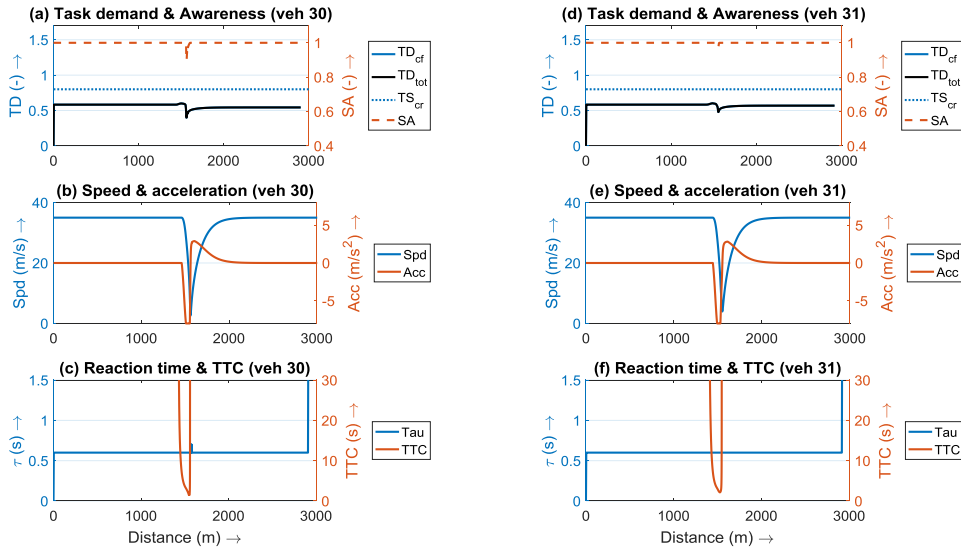
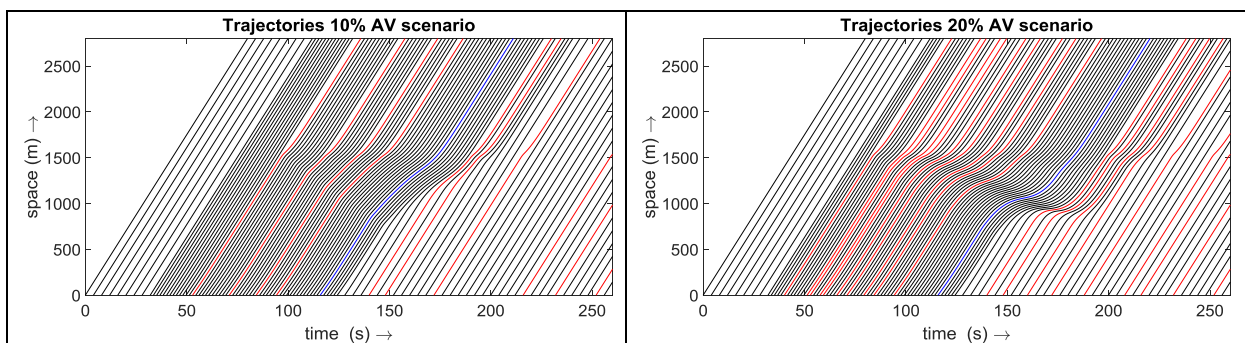


Figure 11: Vehicle and human factor variables - reference 1500veh/h scenario

As far as absolute values of the variables are concerned here, we realise these may not completely represent reality and are in some cases influenced by arbitrary choices. For example, the reaction time due to the cognitive process near a value 0.6 sec may be argued to be higher under normal conditions (note: the total reaction time that is often reported is higher due to the time required to perform physical actions). At the moment, we doubt that accurate and unequivocal values and functions can be given. As far as the demonstration of the framework is concerned, this is also not necessary. The results of the case are further discussed in Section 6.

5.2 Case 2: Location specific transition of control

The second case considers multiple ToC's at a single location over multiple AVs. The traffic demand is set at 2200 veh/hr/lane and drops at a certain point in time to 900 veh/hr/lane to let congestion disperse. Six scenarios are considered, in which different penetration rates of AVs are used: 10, 20, 40, 60, 80 & 100%. The sequence of AVs in traffic is selected randomly. The effect on traffic flow is shown in the trajectory plots in Figure 12a-f, where the red trajectories indicate an AV.



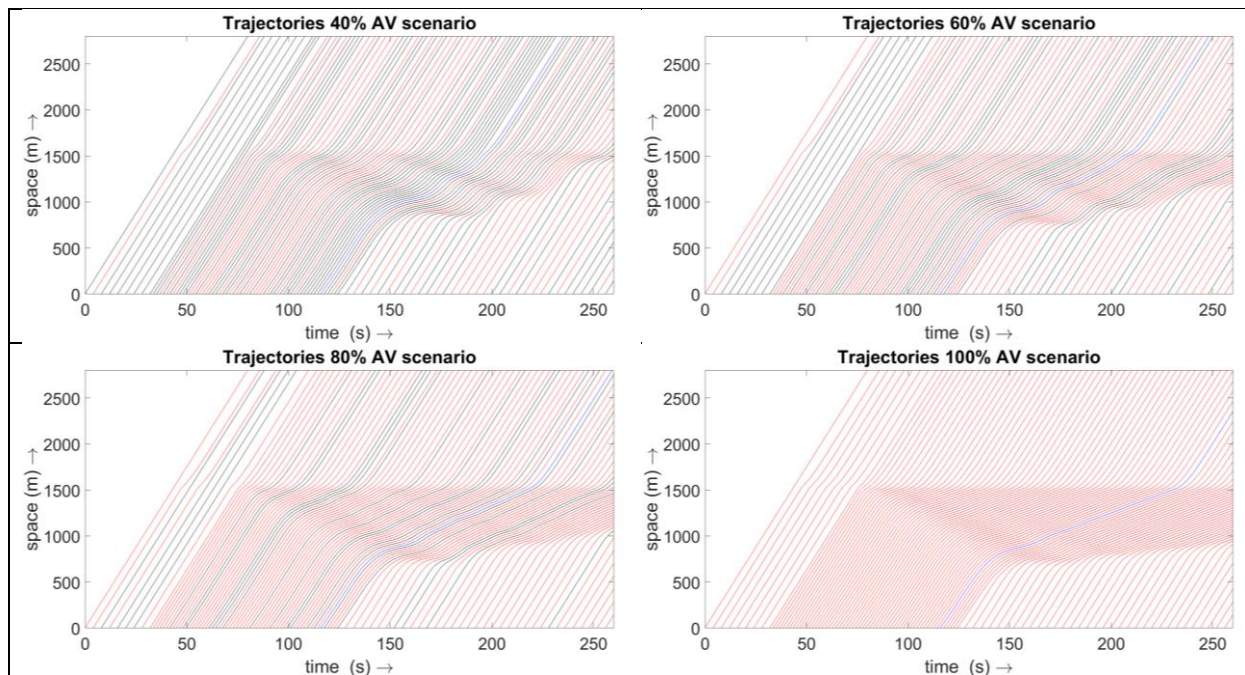


Figure 12: Case 2 vehicle trajectories;

Top-left to bottom-right AV penetration: a) 10%, b) 20%, c) 40%, d) 60%, e) 80%, f) 100%

In this case, there is no physical disturbance, but any effect on traffic comes directly from the ToC. In Figure 12a, it is clear that the manually driven vehicles can proceed along the corridor without any hindrance prior to the first ToC. At the point that the first ToC takes place, we see a small increase in the time-headway on front of the AV, which the AV cannot make up thereafter as both vehicle are driving at their desired speed and maximum speed limits set in the simulation. We see this same increase for all ToC's. Figure 13 shows the HF and vehicle dynamics of the blue vehicle from Figure 12a that also makes a ToC. Prior to the ToC, the TD_{tot} is low and when the TOR is made, we see the same spike in the TD_{tot} due to the TD_{ToC} and TD_{CF} . The SA is initially low and only starts to rise once the TD_{tot} starts to drop again to a stable value. The low SA results in a higher RT (see Figure 12c), which quickly returns to the default reaction time value once the SA increases. The consequence of a low SA, leads to an uncertain or incorrect instantaneous perception of the driver in regard to their environment. This leads to compensative measures that veer on the side of risk avoidance. As a consequence, the driver initially performs a sharp reactive braking manoeuvre, which quickly subsides, as the driver becomes more aware with a higher SA. This exact mechanism is assumed, and is known to take place with some drivers, but will definitely vary per driver and with other variables. The assumption suffices to demonstrate the working of the framework. In Figure 12, the presence of the congestion shockwaves are also visible for the AV (Figure 13a-c) and for an arbitrary manual driver (Figure 13d-f). The effect of this process on traffic flow is therefore one that leads to a disturbance. In this high volume traffic, such a small disturbance leads to congestion shockwaves. In the 10% scenario, this is a single and minor congestion shockwave. While we see for increasing penetration of AVs, that multiple and more severe shockwaves are created with more expansive congestion. Figure 14 shows the effect that this has on the traffic flow along the corridor. The travel time profiles clearly show that the increased level of disturbance with a higher penetration rate leads to higher travel times along the corridor as a consequence. We do reiterate though that the reaction by the AV driver at the ToC is only one assumed and viable reaction, and that the results on traffic flow are purely indicative for the working of the framework and not at all the effects that AVs and ToC may have on traffic flow.

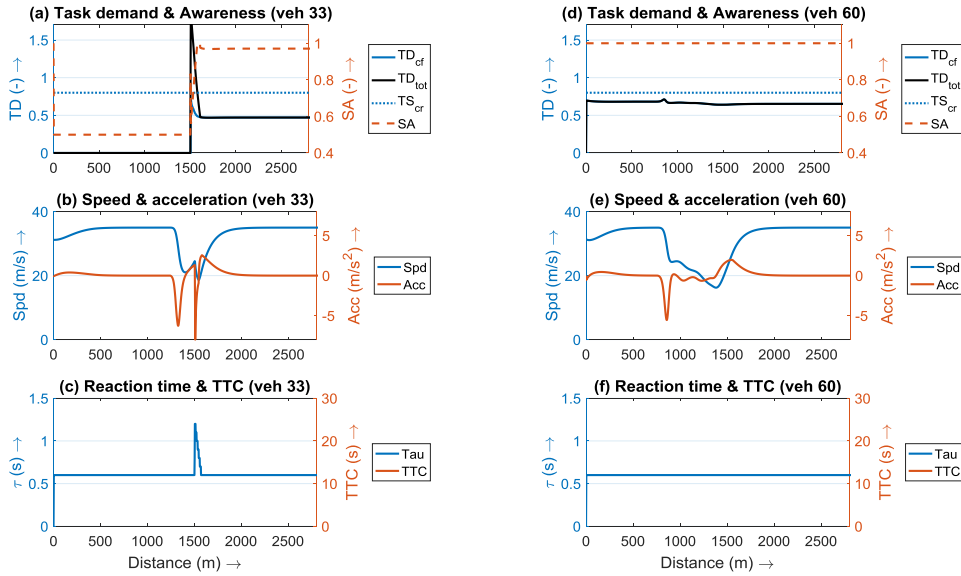


Figure 13: Vehicle and human factor variables - Case 2 example (10% AV scenario)

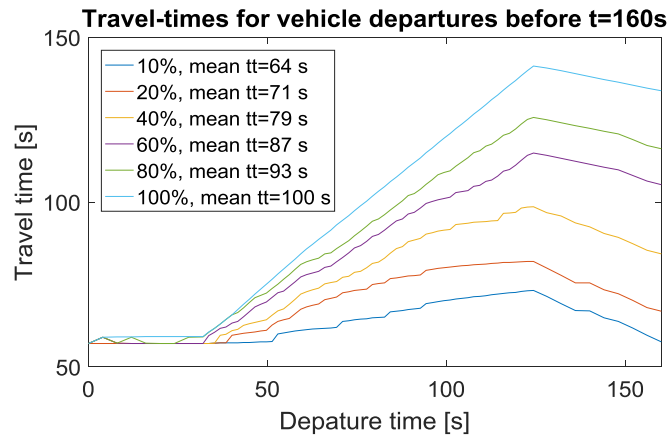


Figure 14: Corridor travel times for Case 2, measured from location 0-2000m.

6 Discussion and conclusions

In this section, we discuss the potential of the extended framework in regard to the results from the two cases that are presented in the previous section. The purpose of the cases is to demonstrate the workings of the framework applied to AVs and the feasibility of it for use in practical modelling. These are discussed in the first sub-section along with an initial validation of the outcomes against other literature and findings elsewhere. Due to the application of constructs from behavioural psychology and limited quantitative evidence of the HF mechanisms, many assumptions have had to be made. These assumptions do lead to limitations in the use of the model as demonstrated in this paper. While all assumptions that were made are feasible and logical, many are arbitrary due to a lack of further evidence. These are discussed in the second sub-section. Finally in the last sub-section, we consider further avenues for further research that exist.

6.1 Findings and validation

The cases are used to demonstrate that the presented framework is capable of simulating the interactive effects of humans with AVs for a commonly occurring process for lower level AVs, namely that of Transition of Control (ToC). This is the first and main finding from this contribution, that this

process can be simulated using this approach. The results from the first case showed the human process that may be present when assuming control of an AV, depicted in task demand and situational awareness. Although many different processes may be possible, the applied assumptions for the applied functions, such as FDTD or reaction times, were feasible and applicable (this was shown in Sections 3.2 and 4.3). The results are also feasible and acceptable in line with literature. Upon a takeover request, the driver initially requires time to acquire this new task and to become aware of the actual driving environment (Eriksson et al. 2017b). The initial reaction by the driver leads to a higher TD over TC. In literature, it is broadly accepted that a higher reaction time is initially required (Eriksson et al. 2017b; Lu et al. 2015; Varotto et al. 2019), which is found in the simulation after the time of ToC. This has also been shown to lead to an initial decrease in speed before full control is assumed (Varotto et al. 2019), which we see from the simulation. Once control is obtained and maintained, a driver's TD and SA will generally return to normal values, which we saw during the second case. A second finding is that the framework can be applied to evaluate the broader traffic flow effects of such human-AV interaction on traffic flow. This is especially visible from case 2, in which an infrastructural influence on the AVs was demonstrated and showed the broader traffic effects and the occurrence of congestion shock-waves. This was obtained, even without consideration of traffic heterogeneity, which may exasperate the effects further. As we mentioned in Section 5.2, the quantitative results of case two should not be taken as a truth about the traffic flow effects of AVs or ToC's, as the model was not calibrated against data and was setup with minimal stochasticity, contrary to what may be expected in practice. This was required to demonstrate the validity of the model, without including too many 'disturbances'. The extended framework therefore has a potentially valuable role to play in the future, in which AVs are going to become more available, but are going to have complex interactions with human drivers. By capturing these interactions endogenously at their source, the real effects can be produced and analysed more so than by exogenous application of parameters that relies on the input it is actually trying to produce.

Therefore, following these recent developments in traffic flow modelling and the ongoing developments in driver psychology and human factors, we propose a novel simulation extension that allows both automated and conventionally driven vehicles to be collectively considered, making use of explicit and endogenous human driving behaviour for driving and interaction with AVs. This contribution also includes an explicit consideration of an important aspect of initial automated driving, namely that of ToC, which is otherwise difficult to accurately model with other existing approaches.

6.2 Limitations

While we have given a clear demonstration of the extended frameworks ability to allow simulation of AV-human driver interactions, we have done so by making a large number of assumptions. It is unavoidable to make these assumptions for a few reasons, which we will now discuss as well as give potential implications thereof. The first main reason is the very essence of human psychology that is difficult if sometimes impossible to capture in quantitative functions. Many constructs have been proposed, such as those by Endsley (1995) and Fuller (2005), which we have used as a basis here. These in themselves, give indications of relationships between various aspects of the (traffic) environment, a person's cognitive state and abilities, but rarely can prove explicit functions between them. Therefore, applying the functions, as in Equations 8-10, means assuming a specific relationship that quantitatively may seem acceptable, when considering evidence from literature, but cannot be claimed in any way to be generically valid under all possible variables that influence a human. For this reason, we allow these functions to remain as inputs for the framework with the hope that cognitive or behavioural psychologists with more understanding of these processes can validate or propose other or more suitable functions. The second main reason for applying certain assumptions focusses on a lack of ground truths in regard to automated driving, and again in regard to human factors. AVs are currently not on our roads in any great numbers and explicit evidence on the wider implications on human behaviour and traffic flow in practice are limited. We do however have access to a broad

amount of literature regarding experiments that can give indications to these processes. This has been used to construct the framework and apply initial parameter values. These give some sort of indication, but does not let full practice validation take place.

In regard to the cases, we have also initially kept the setup limited to allow the explicit effects of the human factors to be visible. One main assumption there was assuming homogenous driver behaviour and traffic flow. This allowed the effects of the HF to be clear and undistorted by potential distributions that may occur from heterogeneity.

6.3 Future research

With the introduction of this extended framework, a large number of new possibilities are opened up. At the same time, there are possibilities to expand and improve on the described limitations. These give way to potential avenues for future research. First of all, there is much happening in regard to human factors research in the traffic domain (Meyer 2019). This will serve to obtain greater certainty and insights into the behavioural process that occur with drivers, both under normal driving conditions and in regard to automation. We don't readily expect that explicit functions of behavioural processes will be available, but we do encourage the domain to take up the challenge further to give more possibilities to allow quantification of the cognitive processes in human factors. On a similar note, continuation of empirical research is required to allow greater ground truths into the processes to be derived. Again, this is required for manual driving, but also increasingly for human driving with automation. Empirical evidence is not only required from a cognitive point of view, but also in regard to vehicle dynamics and intervehicle interactions. Much of this evidence will only start to become available with larger scale experiments with AVs and when AVs take up a greater penetration rate in existing traffic. In regard to the modelling framework presented here, we also make some recommendations for future research. The assumptions that have been made in regard to the functions should be tested further and further explored to see how valid they are and how they can be improved. Also, the process in the framework that considers how task demand is calculated using different tasks should be further elaborated. An assumption that tasks are additive is not correct, although not influential in the cases applied here, an improved process is required there. Other relationships within the framework should also be further scrutinised for validity and in search of improved structure as we do not claim the current framework to be complete, but merely to offer a solid begin to AV-human interaction for simulation.

6.4 Conclusions

This paper presents a novel approach to modelling automated vehicles, which includes important aspects of human driving behaviour. This is based on recent developments in traffic flow modelling and the ongoing developments in driver psychology and human factors that opens the door to a more endogenous and human factor inclusive way of considering traffic simulation. We argue that inclusion of human factors in simulation, which considers mixed automated and conventional traffic, is required to capture the interactive effects that govern vehicle dynamics in traffic flow. The presented extended framework includes human factors through consideration of driver task demands and situation awareness and the use of fundamental diagrams of task demand. The framework is demonstrated in two experimental cases that show the face validity of the approach. Recommendations are made to further expand the approach and in regard to the applied inputs from the domain of driving behaviour. Many of these recommendations relate to the many assumptions that are required to be able to effectively apply the approach in practice. However, with increasing amount of research ongoing in regard to human factors in driving and vehicle automation, and with increasing evidence of automated vehicle dynamics and interactions in mixed traffic becoming available, we argue that many of the assumption can be validated or adjusted in the coming years.

Acknowledgments

This work is partly funded through the research programme Meaningful Human Control over Automated Driving Systems with project number MVI.16.044, which is financed by the Netherlands Organisation for Scientific Research (NWO).

List of Acronyms

AV	Automated Vehicle	RT	Reaction Time
ADCS	Automated driving control system	SA	Situational Awareness
ADS	Automated Driving System	SAE	Society of Automotive Engineers
CF	Car Following	TC	Task Capacity
	Fundamental Diagram of Task	TCI	Task Capacity Interface
FDTD	Demand	TD	Task Demand
FOT	Field Operatoinal Test	ToC	Transition of Control
HAD	Highly Automated Driving	TOR	Take-over Request
HDV	Human Driven Vehicle	TS	Task Saturation
HF	Human Factors	TTC	Time to Collision
HMI	Human Machine Interface	WL	Work Load
IDM(+)	Intelligent Driver Model (plus)		

References

- Adell, E., A. Várhelyi, M. D. Fontana, L. Bruel, and M. Dalla Fontana. 2008. 'Test of HMI alternatives for driver support to keep safe speed and safe distance-A simulator study', *The Open Transportation Journal*, 2: 53-64.
- Axelsson, J. 2017. 'Safety in vehicle platooning: A systematic literature review', *IEEE Transactions on Intelligent Transportation Systems*, 18: 1033-45.
- Bando, M., K. Hasebe, K. Nakanishi, and A. Nakayama. 1998. 'Analysis of optimal velocity model with explicit delay', *Physical Review E*, 58: 5429.
- Bellet, T., P. Mayenobe, J.-C. Bornard, D. Gruyer, and B. Claverie. 2012. 'A computational model of the car driver interfaced with a simulation platform for future Virtual Human Centred Design applications: COSMO-SIVIC', *Engineering Applications of Artificial Intelligence*, 25: 1488-504.
- Cacciabue, P. C., and O. Carsten. 2010. 'A simple model of driver behaviour to sustain design and safety assessment of automated systems in automotive environments', *Applied ergonomics*, 41: 187-97.
- Calvert, S. C., D. D. Heikoop, and B. Van Arem. 2019a. 'Core components framework of automated driving systems with meaningful human control', *Theoretical Issues in Ergonomics Science*.
- Calvert, S. C., G. Mecacci, B. van Arem, F. Santoni de Sio, D. D. Heikoop, and M. Hagenzieker. 2019b. 'Gaps in the control of automated vehicles on roads', *IEEE Intelligent Transportation Systems Magazine*.
- Calvert, S. C., W. J. Schakel, and J. W. C. van Lint. 2017. 'Will Automated Vehicles Negatively Impact Traffic Flow?', *Journal of Advanced Transportation*, 2017: 17.
- Carsten, O., F. C. Lai, Y. Barnard, A. H. Jamson, and N. Merat. 2012. 'Control task substitution in semiautomated driving: Does it matter what aspects are automated?', *Human factors*, 54: 747-61.
- Casner, S. M., E. L. Hutchins, and D. Norman. 2016. 'The challenges of partially automated driving', *Communications of the Acm*, 59: 70-77.
- Davis, L. 2003. 'Modifications of the optimal velocity traffic model to include delay due to driver reaction time', *Physica A: Statistical Mechanics and its Applications*, 319: 557-67.

- de Waard, D., A. Kruizinga, and K. A. Brookhuis. 2008. 'The consequences of an increase in heavy goods vehicles for passenger car drivers' mental workload and behaviour: a simulator study', *Accident analysis & prevention*, 40: 818-28.
- De Winter, J. C., R. Happee, M. H. Martens, and N. A. Stanton. 2014. 'Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence', *Transportation Research Part F: Traffic Psychology and Behaviour*, 27: 196-217.
- Endsley, M. R. 1995. 'Toward a theory of situation awareness in dynamic systems', *Human Factors*, 37: 32-64.
- Endsley, M. R. 1999. 'Level of automation effects on performance, situation awareness and workload in a dynamic control task', *Ergonomics*, 42: 462-92.
- Eriksson, A., and N. A. Stanton. 2017a. 'Driving performance after self-regulated control transitions in highly automated vehicles', *Human factors*, 59: 1233-48.
- Eriksson, A., and N. A. Stanton. 2017b. 'Takeover time in highly automated vehicles: noncritical transitions to and from manual control', *Human factors*, 59: 689-705.
- Fritzsche, H.-T. 1994. 'A model for traffic simulation', *Traffic Engineering+ Control*, 35: 317-21.
- Fuller, R. 2005. 'Towards a general theory of driver behaviour', *Accident analysis & prevention*, 37: 461-72.
- Fuller, R. 2011. 'Driver control theory: From task difficulty homeostasis to risk allostasis.' in, *Handbook of Traffic Psychology*.
- Gazis, D. C., R. Herman, and R. W. Rothery. 1961. 'Nonlinear follow-the-leader models of traffic flow', *Operations research*, 9: 545-67.
- Gold, C., D. Damböck, L. Lorenz, and K. Bengler. 2013. "'Take over!' How long does it take to get the driver back into the loop?" In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 1938-42*. SAGE Publications Sage CA: Los Angeles, CA.
- Hamdar, S., M. Treiber, H. Mahmassani, and A. Kesting. 2008. 'Modeling driver behavior as sequential risk-taking task', *Transportation Research Record: Journal of the Transportation Research Board*: 208-17.
- Hamdar, S. H., H. S. Mahmassani, and M. Treiber. 2015. 'From behavioral psychology to acceleration modeling: Calibration, validation, and exploration of drivers' cognitive and safety parameters in a risk-taking environment', *Transportation Research Part B: Methodological*, 78: 32-53.
- Hoogendoorn, R., B. van Arem, and S. Hoogendoorn. 2014. 'Automated Driving, Traffic Flow Efficiency, and Human Factors: Literature Review', *Transportation Research Record: Journal of the Transportation Research Board*: 113-20.
- Kerner, B. S., and S. L. Klenov. 2006. 'Deterministic microscopic three-phase traffic flow models', *Journal of Physics A: mathematical and general*, 39: 1775.
- Kesting, A., M. Treiber, M. Schönhof, F. Kranke, and D. Helbing. 2007. 'Jam-avoiding adaptive cruise control (ACC) and its impact on traffic dynamics.' in, *Traffic and Granular Flow'05* (Springer).
- Klunder, G., M. Li, and M. Minderhoud. 2009. 'Traffic flow impacts of adaptive cruise control deactivation and (Re) activation with cooperative driver behavior', *Transportation Research Record: Journal of the Transportation Research Board*: 145-51.
- Konstantopoulos, P., P. Chapman, and D. Crundall. 2010. 'Driver's visual attention as a function of driving experience and visibility. Using a driving simulator to explore drivers' eye movements in day, night and rain driving', *Accident analysis & prevention*, 42: 827-34.
- Kuderer, M., S. Gulati, and W. Burgard. 2015. "Learning driving styles for autonomous vehicles from demonstration." In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, 2641-46. IEEE.
- Kyriakidis, M., J. C. de Winter, N. Stanton, T. Bellet, B. van Arem, K. Brookhuis, M. H. Martens, K. Bengler, J. Andersson, and N. Merat. 2017. 'A human factors perspective on automated driving', *Theoretical Issues in Ergonomics Science*: 1-27.

- Laval, J. A., and L. Leclercq. 2010. 'A mechanism to describe the formation and propagation of stop-and-go waves in congested freeway traffic', *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 368: 4519-41.
- Lee, Y. M., and E. Sheppard. 2017. 'Differences in gap acceptance for approaching cars and motorcycles at junctions: What causes the size-arrival effect?', *Transportation Research Part F: Traffic Psychology and Behaviour*, 50: 50-54.
- Lefèvre, S., A. Carvalho, Y. Gao, H. E. Tseng, and F. Borrelli. 2015. 'Driver models for personalised driving assistance', *Vehicle System Dynamics*, 53: 1705-20.
- Liu, B.-S., and Y.-H. Lee. 2006. 'In-vehicle workload assessment: effects of traffic situations and cellular telephone use', *Journal of safety research*, 37: 99-105.
- Louw, T., G. Kountouriotis, O. Carsten, and N. Merat. 2015. "Driver Inattention During Vehicle Automation: How Does Driver Engagement Affect Resumption Of Control?" In *4th International Conference on Driver Distraction and Inattention (DDI2015)*, Sydney.
- Lu, Z., and J. de Winter. 2015. 'A review and framework of control authority transitions in automated driving'.
- Merat, N., and A. H. Jamson. 2009. "How do drivers behave in a highly automated car." In *Proceedings of the 5th international driving symposium on human factors in driver assessment, Training and Vehicle Design*, 514-21.
- Merat, N., A. H. Jamson, F. C. Lai, and O. Carsten. 2012. 'Highly automated driving, secondary task performance, and driver state', *Human factors*, 54: 762-71.
- Merat, N., A. H. Jamson, F. C. Lai, M. Daly, and O. M. Carsten. 2014. 'Transition to manual: Driver behaviour when resuming control from a highly automated vehicle', *Transportation Research Part F: Traffic Psychology and Behaviour*, 27: 274-82.
- Meyer, G., and Sven Beiker, eds. 2019. *Road Vehicle Automation 5* (Springer International Publishing).
- Milanés, V., S. E. Shladover, J. Spring, C. Nowakowski, H. Kawazoe, and M. Nakamura. 2014. 'Cooperative adaptive cruise control in real traffic situations', *IEEE Transactions on Intelligent Transportation Systems*, 15: 296-305.
- Newell, G. F. 2002. 'A simplified car-following theory: a lower order model', *Transportation Research Part B: Methodological*, 36: 195-205.
- Nilsson, R. 2000. 'Drivers' impressions of front and rear gaps in queues', *Ergonomics*, 43: 1985-2000.
- Parasuraman, R., T. B. Sheridan, and C. D. Wickens. 2000. 'A model for types and levels of human interaction with automation', *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans*, 30: 286-97.
- Pipes, L. A. 1953. 'An operational analysis of traffic dynamics', *Journal of applied physics*, 24: 274-81.
- Poulter, D. R., P. Chapman, P. A. Bibby, D. D. Clarke, and D. Crundall. 2008. 'An application of the theory of planned behaviour to truck driving behaviour and compliance with regulations', *Accident analysis & prevention*, 40: 2058-64.
- SAE. 2018. "SAE J3016: Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems." In.: On-Road Automated Vehicle Standards Committee SAE. .
- Saffarian, M., J. C. de Winter, and R. Happee. 2012. "Automated driving: human-factors issues and design solutions." In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2296-300. Sage Publications Sage CA: Los Angeles, CA.
- Saifuzzaman, M., and Z. Zheng. 2014. 'Incorporating human-factors in car-following models: a review of recent developments and research needs', *Transportation Research Part C: Emerging Technologies*, 48: 379-403.
- Saifuzzaman, M., Z. Zheng, M. M. Haque, and S. Washington. 2017. 'Understanding the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level', *Transportation Research Part B: Methodological*, 105: 523-38.
- Sanchez, F., R. Blanco, and J. L. Diez. 2016. 'Better together: cooperative technologies will be vital to the development of highly autonomous vehicles operating in complex urban environments', *Vision Zero International*.

- Schakel, W., V. Knoop, and B. van Arem. 2012. 'Integrated Lane Change Model with Relaxation and Synchronization', *Transportation Research Record: Journal of the Transportation Research Board*, 2316: 47-57.
- Shladover, S. E. 2009. 'Cooperative (rather than autonomous) vehicle-highway automation systems', *Intelligent Transportation Systems Magazine, IEEE*, 1: 10-19.
- Sjoberg, K., P. Andres, T. Buburuzan, and A. Brakemeier. 2017. 'Cooperative intelligent transport systems in Europe: current deployment status and outlook', *IEEE Vehicular Technology Magazine*, 12: 89-97.
- Stanton, N. A., and M. S. Young. 2005. 'Driver behaviour with adaptive cruise control', *Ergonomics*, 48: 1294-313.
- Teh, E., S. Jamson, O. Carsten, and H. Jamson. 2014. 'Temporal fluctuations in driving demand: The effect of traffic complexity on subjective measures of workload and driving performance', *Transportation Research Part F: Traffic Psychology and Behaviour*, 22: 207-17.
- Thiffault, P., and J. Bergeron. 2003. 'Monotony of road environment and driver fatigue: A simulator study', *Accident Analysis and Prevention*, 35: 381-91.
- Treiber, M., A. Hennecke, and D. Helbing. 2000. 'Congested traffic states in empirical observations and microscopic simulations', *Physical Review E*, 62: 1805.
- Underwood, G. 2007. 'Visual attention and the transition from novice to advanced driver', *Ergonomics*, 50: 1235-49.
- van Lint, J. W. C., and S. C. Calvert. 2018. 'A generic multi-level framework for microscopic traffic simulation—Theory and an example case in modelling driver distraction', *Transportation Research Part B: Methodological*, 117: 63-86.
- van Wageningen-Kessels, F., H. Van Lint, K. Vuik, and S. Hoogendoorn. 2015. 'Genealogy of traffic flow models', *EURO Journal on Transportation and Logistics*, 4: 445-73.
- Varotto, S. F., H. Farah, K. Bogenberger, B. Van Arem, and S. P. Hoogendoorn. 2019. 'Adaptations in driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road study', *Transportmetrica A: Transport Science*, in publication.
- Varotto, S. F., H. Farah, T. Toledo, B. van Arem, and S. P. Hoogendoorn. 2018. 'Modelling decisions of control transitions and target speed regulations in full-range Adaptive Cruise Control based on Risk Allostasis Theory', *Transportation Research Part B: Methodological*, 117: 318-41.
- Wickens, C. D. 2008a. 'Multiple resources and mental workload', *Human factors*, 50: 449-55.
- Wickens, C. D. 2008b. 'Situation Awareness: Review of Mica Endsley's 1995 Articles on Situation Awareness Theory and Measurement', *HUMANFACTORS*, 50: 397-403.
- Wickens, C. D., J. G. Hollands, S. Banbury, and R. Parasuraman. 2015. *Engineering psychology & human performance* (Psychology Press).
- Wiedemann, R. 1974. "Simulation des Straßenverkehrsflusses." In.: University of Karlsruhe.
- Wong, J.-T., and S.-H. Huang. 2009. "Modeling driver mental workload for accident causation and prevention." In *Proceedings of the Eastern Asia Society for Transportation Studies Vol. 7 (The 8th International Conference of Eastern Asia Society for Transportation Studies, 2009)*, 365-65. Eastern Asia Society for Transportation Studies.
- Xiao, L., M. Wang, and B. van Arem. 2017. 'Realistic car-following models for microscopic simulation of adaptive and cooperative adaptive cruise control vehicles', *Transportation Research Record: Journal of the Transportation Research Board*: 1-9.
- Young, K. L., P. M. Salmon, and M. Cornelissen. 2013. 'Missing links? The effects of distraction on driver situation awareness', *Safety Science*, 56: 36-43.
- Zeeb, K., A. Buchner, and M. Schrauf. 2015. 'What determines the take-over time? An integrated model approach of driver take-over after automated driving', *Accident analysis & prevention*, 78: 212-21.
- Zhang, B., E. S. Wilschut, D. M. Willemsen, T. Alkim, and M. H. Martens. 2017. "The Effect of See-Through Truck on Driver Monitoring Patterns and Responses to Critical Events in Truck

Platooning." In *International Conference on Applied Human Factors and Ergonomics*, 842-52. Springer.