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Anticipation Reliance as compensation mechanism for potential task overload**

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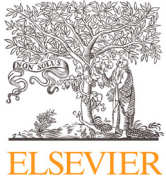
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A generic multi-scale framework for microscopic traffic simulation part II – Anticipation Reliance as compensation mechanism for potential task overload



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ABSTRACT

The inclusion of human factors (HF) in mathematical models is proving crucial to allow complex driving behaviour and interactions to be explicitly considered to capture driving phenomena. An important area where such integration is required is for the role of anticipation by drivers to compensate for critical traffic situations. In this paper, we introduce the concept of Anticipation Reliance (AR), which acts as a demand lowering compensative effect for the driving task by relying more on anticipation. We implement AR in a generic multi-scale microscopic traffic modelling and simulation framework to explore and explain the effects of HF on traffic operations and safety in critical traffic situations. This concept addresses a disparity in the description of driver workload in relation to the execution of driving tasks in regard to the confidence that drivers place on tasks that are sub-consciously catered for. The crossover from HF to a mathematical description of this role of AR introduces a ground-breaking concept that explains and models the mechanisms that allow drivers to compensate and avoid accidents in many circumstances, even when driving errors or sub-optimal driving performance occurs. By and large, the HF effects can be subdivided in effects on perception and anticipation; effects on sensitivity and response to stimuli; and effects on personal attributes and characteristics. A key aspect of the framework are two intertwined driver-specific mental state variables—total workload and awareness—that bridge between classic collision-free idealized models for lane changing and car following, and HF models that explain under which conditions the performance of drivers deteriorates in terms of reaction time, sensitivity to stimuli or other parameters. In this paper, we focus on the awareness construct, as described by AR, and explore the effects. We prove the effectiveness of the approach with a case example that demonstrates the ability of the model to dissect a complex traffic situation with both longitudinal and lateral driving tasks, while endogenously considering human factors and that produces accident avoidance and occurrence within the same order of magnitude compared to real traffic accident statistics.

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1. Introduction

While millions of road accidents occur each year, this number could well be significantly higher if drivers generally were not as good as they are at compensating for errors and unexpected changes in their driving environments (Strayer and Drew, 2004; Wickens et al., 2015; De Raedt and Ponjaert-Kristoffersen, 2000; Schömig, Metz, and Krüger, 2011). Humans are generally very good at perceiving and interpreting their environments and understanding and anticipating future states and events (Endsley, 1995; Kunde, Elsner, and Kiesel, 2007). By doing so, many accidents are prevented and can be categorized as near-misses (McKenna, Horswill, and Alexander, 2006). These mechanisms are all part of a human's cognitive information processing, which for traffic is often described within the domain of human factors, and which is crucial for understanding driving mechanism for (near)-accidents (Wong and Huang, 2009). These complex cognitive processes are not readily included in traffic modelling and therefore restrict the capabilities of traffic models to accurately capture these compensatory actions and give accurate representations of driver-vehicle dynamics. A major part of this human behaviour is the ability of drivers to anticipate. This offers a driver the ability to deal with situations that may have been physically and mentally too challenging otherwise. In our original paper (van Lint and Calvert, 2018), we introduced a generic framework that allows explicit endogenous consideration of driver cognition and interaction with the driving tasks and execution. A logical and important expansion of this framework is the inclusion of the role of anticipation to allow a driver to take on more complex task combinations and to compensate for cognitive overloading. This is the main contribution of this paper, to introduce Anticipation Reliance as a concept that allows this and that can be applied in human factor based microsimulation to achieve driver compensatory behaviour and to explain how drivers can deal with multiple tasks without always becoming cognitively oversaturated. We present the concept in Section 4 of the paper, while the rest of the introduction highlights the necessity and current practice in regard to traffic modelling and consideration of driver behaviour.

Human behaviour lies at the core of traffic flow, by definition, as vehicle movements directly relate to human control of the vehicle. Therefore, the basic assumptions of any traffic related model must take this human driving behaviour into account. Historically, this has been achieved by basing general movement of vehicles in traffic flow on generic empirically derived mechanisms that are found in traffic flow and have been developed into the core of traffic flow theory (van Wageningen-Kessels et al., 2015). This basic core of traffic flow theory can be found in work by (Greenshields, 1934), (Lighthill and Whitham, 1955; Richards, 1956) (and many others) on the fundamental relation and the fluid dynamical description of traffic. Up to this day, many if not most traffic (simulation) models are (in)directly based on these theories. While macroscopic modelling continued its development aimed at capturing the traffic dynamics on an aggregate flow level, in which individual vehicle movements were not required, microscopic modelling aimed to describe individual vehicle movement in relation to each other and the infrastructure. Through the years, we have seen safe-distance car following (CF) models (Pipes, 1953; Newell, 2002; Laval and Leclercq, 2010) that assume drivers maintain a large enough distance headway in case the leader brakes at maximum deceleration; optimal velocity models (Bando et al., 1998; Davis, 2003) that assume drivers accelerate to their optimal velocity as a function of the distance headway; whereas approaches in the more general group of stimulus-response models (Gazis, Herman, and Rothery, 1961; Treiber, Hennecke, and Helbing, 2000; Kerner and Klenov, 2006; Chen et al., 2014) make assumptions on how drivers adapt their response (acceleration) to a range of different stimuli (distance headway, speed differences).

In many of the mainstream models, mechanisms are constructed that allow vehicles to respond to each other in a reasonable manner and one that satisfies general empirical observations. However, the place of human factors in the models remains consigned to the direct empirical responses that are observed. While giving a good overall representation of traffic, this lacks the detail and possibility to explicitly consider the endogenous effects of human cognitive behaviour that lies at the heart of many details in traffic flow. It are these details that are believed to result in many traffic phenomena that can be observed on roads, such as hysteresis, congestion in heterogeneous traffic flow, accidents, etc. Increasingly, there is a desire and need to be able to realistically predict potentially unsafe traffic operations, and the corresponding indicators (such as statistics of accidents and surrogate safety measures) (Mullakkal-Babu et al., 2017), to be able to study risk and accident impact. Also the emergence of vehicle automation is placing great demands on traffic simulation. The differences between (partially) automated vehicles and conventional vehicles can in a large part be attributed to the 'details' of human driving behaviour, that goes further than general traffic flow characteristics (Calvert et al., 2018; Sharma et al., 2017). In all of the previously given examples, the role of driver perception, anticipation, comprehension, ability, training, current mental state, and so on, is of great importance to be able to accurately model the underlying behavioural dynamics and effectively analyse the mentioned areas.

Some models have managed to include certain aspects of more detailed human behaviour in simulation, such as so-called psycho-spacing (or action point) models (Wiedemann, 1974; Fritzsche, 1994) that incorporate drivers' inertia to observe and respond to small changes in stimuli; and more recently multi-anticipatory models (Hoogendoorn, Ossen, and Schreuder, 2006; Treiber, Kesting, and Helbing, 2006; Hoogendoorn, Ossen, and Schreuder, 2007) that include terms for anticipation of drivers to traffic conditions further downstream. While these models do improve on realistic human driving behaviour, the models remain focussed on external responses to the driving environment, rather than endogenous cognitive responses of drivers. Several approaches have already been proposed in this direction (Saifuzzaman and Zheng, 2014), e.g. using prospect theory (in which drivers way faster travel time against the risk of rear-end crashes (Hamdar, Mahmassani, and Treiber, 2015; Hamdar et al., 2008; Sharma et al., 2019)); considering bounded rationality (Tang, Zhang, and Liu, 2017), and using Fullers' Risk Allostasis Theory (Fuller, 2011) (in which risk taking and driver response is considered a result of comparing subjec-

tive task demand and task capacity using the so-called Task-Capability-Interface (TCI) model (e.g. (Hoogendoorn et al., 2013; Saifuzzaman et al., 2015), and (Saifuzzaman et al., 2017)). However, more behavioural sophistication comes at a methodological and computational price, in terms of model identification, calibration and validation efforts; and computational efficiency. Therefore, the challenge for our community in the coming years, is to augment existing CF and Lane Change (LC) models with a range of explanatory (HF) mechanisms that (a) endogenously predict where and under which circumstances drivers e.g. make errors, take more (or less) risks, suffer from longer reaction times; use (b) mathematics and simulation logic that is tractable and simple enough so that large-scale simulation is (still) possible; while (c) still reproduce plausible vehicle trajectories and (by implication) plausible macroscopic traffic patterns.

Therefore, van Lint and Calvert (2018) proposed a generic multi-level behavioural framework for traffic simulation that explicitly models driver cognitivity and opens the door to model vehicles, not only considering general dynamics or exogenous behavioural effects, but also the underlying constructs of human behaviour that are directly responsible for detailed traffic behaviour and meet the previously discussed conditions. In this contribution we aim to further build on the initial description of the framework and extend it to explicitly consider the role of driver anticipation and perception errors on traffic flow. These driver aspects are of direct importance for maintaining personal safety by means of risk management (Fuller, 2011). But they are also integral in the causality of road accidents and traffic safety. We start by reviewing the influence of anticipation and perception in Section 2. After the methodological description of the model framework with the inclusion of anticipation and perception in Sections 3–4, we demonstrate the application of the framework, using an arbitrary simulation model, to show the validity and relevance in regard to risk, traffic safety and accident modelling in traffic simulation (Section 5). The ability to accurately model these areas in such a way opens up extensive possibilities for the analysis of traffic safety, also especially in regard to vehicle automation. This is further discussed in Section 6.

2. Related work: role of perception and anticipation

Before diving into the modelling framework, it is good to gain a greater understanding of current knowledge in regard to perception, workload and anticipation. Therefore, in this section we take a look at some relevant insights and discussions in regard to this. For the latter, we do this firstly in a broader sense, followed by some considerations in regard to driving.

2.1. Driver perception and tasks

For the best part of the last two decades, the ground-breaking work performed by Endsley (1995) on Situation Awareness (SA) has been held as one of the primary works on human awareness and decision making (Wickens, 2008b). We will also use it here to consider the main aspects of human perception and awareness. SA is loosely defined as “knowing what’s going on” and is more formally defined as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future.” From this definition, it is clear that the concept involves many aspects that humans and human drivers are engaged with.

Three different levels of SA are defined: *perception, comprehension, and projection*. Perception (level 1 SA) involves perceiving the status, attributes and dynamics of specific relevant aspects of a person’s environment. In driving, this may be observing surrounding vehicles and road infrastructure, but also behaviours and movements relating to other vehicles and drivers. Comprehension (level 2 SA) is the process of understanding the perceived level 1 environment. This involves collecting the presence, movements and actions of all perceptions into a single mental world to gain a total understanding of the environment. The final level, level 3, is the prediction of future states and involves creating a future mental world state based on the level 1 (perception) and level 2 (comprehension) of SA. The extent to which a driver can predict future events, either short-term or long-term, depends on a number of aspects, not least the experience of a driver and their current state. A well trained, experienced and focussed driver will be able to process their comprehension of their environment and align this to previous situations to improve their understanding and accuracy of predictions. This may involve various behaviours of driver and vehicles, such as car-following, braking actions or anticipation of lane changes, as some obvious examples. It should also be noted that each of these steps is a personal cognitive process that entails a large degree of subjectivity. The extent to which a driver’s SA is close to a true objective SA again depends on their own state and ability, amongst others. In van Lint and Calvert, (2018), we previously aligned this process to driving and depicted this graphically as shown in Fig. 1.

Following on from a humans SA, which can be seen as a primary human factors process, conscious decisions and actions can be made in an effort to influence one’s own role and standing in the environment. These decisions and actions can be described as the response process, in which drivers act based on the perceived and possibly predicted stimuli (van Lint and Calvert, 2018), see Fig. 2. Clearly, also the response process is subject to driver traits, which encompass all relevant mental states, attitudes, preferences, skills, etc.

Fuller (2005), in his *Task Difficulty Homeostasis*, goes further to describe the process of decisions and actions based on a driver’s perceived Task Difficulty, which is a product of the perceived Task demand and perceived capability and motivation. According to this theory, a driver continuously makes real-time decisions to limit risk and maintain perceived difficulty of driving task within their acceptable limit by adjusting control variables (Fuller, 2011). In such a way, a driver can maintain control over their vehicle in the current temporal environment. If a driver encounters a task demand that is too high, or they have a too low task capability, there may be two possible outcomes. Either the driver’s task capability is exceeded and their driving performance deteriorates through impaired SA and becomes ‘risky’

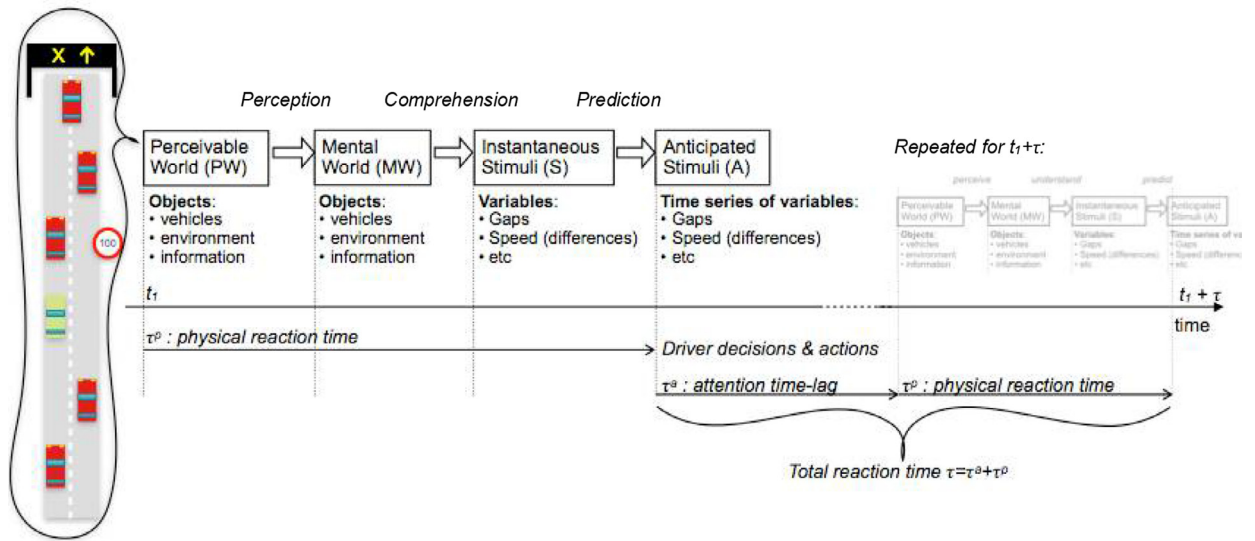


Fig. 1. Conceptual model for awareness based on Endsley (Endsley, 1995; Wickens, 2008c; van Lint and Calvert, 2018).

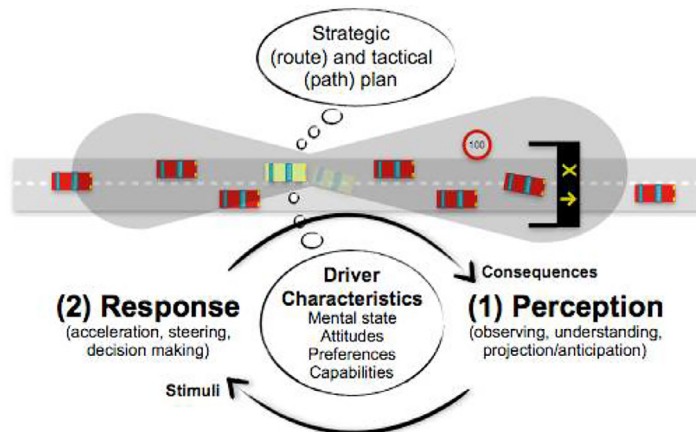


Fig. 2. Driving as a control task (van Lint and Calvert, 2018).

(Fuller, 2005; Wickens and Hollands, 2000), or compensative measures are required by the driver to lower task demand (or increase task capability). Obvious options may be to (temporarily) terminate a non-critical task (Schömig, Metz, and Krüger, 2011) or reduce the load of a task, e.g. by reducing speed or increasing distance. This process has been widely observed and can be described as a form of risk compensation (De Raedt and Ponjaert-Kristoffersen, 2000; Hoyos, 1988; Regan, Lee, and Young, 2008). Another (sub-conscious) process that often occurs before a task critical event is through anticipation of future events. This allows a driver to pro-actively act to reduce risk and task load and potential risk. In the following paragraphs, we dive deeper into this process of anticipation as a potential task compensative process.

2.2. Role of anticipation in general

The previously presented frameworks (Endsley, 1995; Wickens, 2008a) show that anticipation can play a role in reducing the aspect of risk. Anticipation, often referred to as anticipatory response or control, has the ability to alter the state of a cognitive system in such a way that potential threats are essentially neutralised before they are encountered (Fuller, 1984). In the case of driving, this has a particular advantage that if the driver makes an error or mistake, there is still the possibility of error correction (Fuller, 2005). Anticipation plays an important part in this process and has a strong influence on both human perception and task processing. We start by considering anticipation in a broader sense in this sub-section, before elaborating its application to driving in the next.

In general terms, Ekdahl (2000) defines anticipation as “an act of intention”, while Rosen (2012) describes anticipatory systems as “containing a predictive model of itself and/or of its environment, which allows it to change state at an instant

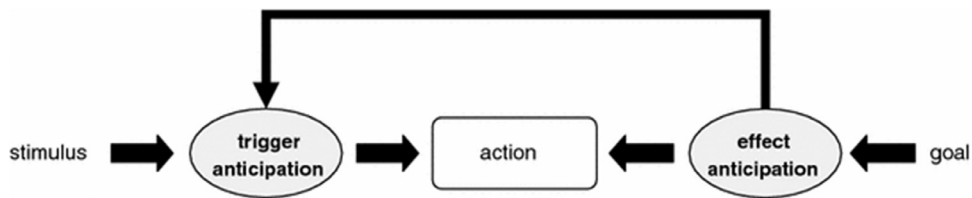


Fig. 3. Weak anticipation (Kunde, Elsner, and Kiesel, 2007).

in accord with the model's predictions pertaining to a latter instant". Klir (2013) bridges these broad definitions and state that such systems "are able to develop a model of their environment and use it in an anticipatory manner". Another similar view is given by Dubois (2003): "An anticipatory system is a system for which the present behaviour is based on past and/or present events but also on future events built from these past, present and future events." Following on from Fuller's definition, Malakis and Kontogiannis (2008) also define anticipation in relation to risk as "A cognitive strategy that enables a controller to timely and accurately detect and respond to a threat." They state that anticipation engages with response planning and is the process of recognizing and preparing for difficult challenges and brings forward the notion of threats. Threats can be defined as events or errors that occur beyond the control of the controller and must be managed in order to maintain the margins of safety (Malakis and Kontogiannis, 2008). This doesn't actually differ too much from the former definitions (Ekdahl, 2000; Klir, 2013; Rosen, 2012), but is given a greater applied focus for a specific state variable, namely risk. From this, it is clear that there is some general consensus on the idea of anticipation, while deviations in its application, either as a descriptive concept or as an internal process, will lead to different applications.

When considering anticipation as a cognitive component in practice, its application in context is of importance. Broad consensus exists that there are generally two different forms of anticipation, namely *strong (or endo-) anticipation* and *weak (or exo-) anticipation* (Dubois, 2003; Nahodil and Vitkú, 2012; Riegler, 2001). Originally coined by Dubois (2003), **Strong anticipation** refers to anticipation which is embedded in a system in regard to its own behaviour. These are processes which occur sub-consciously and are not the result of cognitive reasoning (Riegler, 2001). They therefore do not require task loading based on a person's interpretation of their environment, but are rather 'insight-free' instincts and serve as a priori adaptation to recurring environmental changes (Riegler, 2001). Riegler (2001) goes on to state that there are three types of strong anticipation: inborn, emotional, and intelligent. Inborn anticipation occurs as the result of some phylogenetically acquired patterns. Anticipation is emotional if it is driven by some instinct, such as hunger. Intelligent anticipation is the ability to think of a remote future that does not depend on the current state (Suddendorf, 1994). Strong anticipation is therefore an internal process that is governed by an internal model (Dubois, 2003) or is even part of the physical (cognitive) system and is a consequence of a systems organization (Riegler (2001) refers to this as 'canalization'). The manner of embedding is still an ongoing topic, but goes beyond the scope of this paper.

Weak anticipation refers to anticipation made by a system about external systems and refers to anticipation relating to predictions or expectations. It is clear that weak anticipation involves a conscious process that proceeds through the dynamic system decision process as identified by (Endsley, 1995) in regard to Situation Awareness. This can be referred to as a system based on a model and thus is a model-based prediction and not a system-based prediction, similar to model based control in the traffic domain. There is an obvious reaction to stimulation from an external environment, which leads to a conscious decision to take action, which Kunde, Elsner, and Kiesel (2007) defines as goal-oriented action and determines the motor output. Two types of weak anticipation can be considered (Butz and Hoffmann, 2002; Hoffmann, 2003). The first relates to changes of the perceived world and to the intended effect of the action and thus the goal. The second relates to environmental conditions that have to be met to bring an intended effect into being. The difference is therefore the focus of the anticipation, which is either on the goal or on the environment in regard to anticipation, see Fig. 3. Either way, this process is a conscious one that demands some sort of task loading.

Anticipation evidently has some sort of effect on cognitive workload. Malakis and Kontogiannis (2008) consider anticipation as a cognitive strategy that enables a controller to timely and accurately detect and respond to a threat. Managing workload is also a cognitive strategy that enables a person to timely and accurately sequence the required tasks and respond to interruptions and distractions. From the onset of an event, the workload increases significantly due to a notable increase in the number of tasks, the available time and the importance of the tasks to be completed (Malakis and Kontogiannis, 2008). They further state that workload management, including anticipation, functions as a mental task regulator enabling controllers to cope with the complexity of the situation. Anticipation is a mechanism that can be applied to "deal with real stress" (Conte and Plutchik, 1995) when facing high task demand and can reduce stress of some difficult challenge by anticipating (Cleese and Skynner, 2011; Conte and Plutchik 1995). In such a way, strong anticipation may be applied as a way to reduce task demand and improve cognitive performance. There is also evidence that anticipation tends to improve with age and with experience (Botvinick and Rosen, 2009; Conte and Plutchik, 1995). In regard to weak anticipation, as this makes use of cognitive reasoning, it logically results in a higher level of cognitive demand (Botvinick and Rosen, 2009) and should be seen as an additional cognitive task. It can therefore increase stress, but with potential risk avoidance gains through improved decision making.

2.3. Anticipation in driving

As mentioned, the way anticipation is applied has influence on the effect that it can have and the underlying cognitive process that is followed. Therefore, we now also take time to review literature on how the process of anticipation may be applied to driving.

Anticipation plays a major role in driving as it allows one to make expectations about future demands of a situation, the development of potential dangers and behavioural adaptations that might be necessary (Schömig, Metz, and Krüger, 2011). Anticipation gives a driver the ability to predict the immediate future state of the unfolding road and road user scenario ahead, and in doing so, mitigate potential threats that may occur (Fuller, 2005). Anticipation in driving is mainly controlled by the visual system and includes the perception of upcoming road course, objects and events (Schömig, Metz, and Krüger, 2011). In the first place, this can relate to longitudinal driving, such as car following and free driving. A driver will either maintain visual contact or will perform glances to perceive their environment that can range anywhere from tens of seconds up to 3–4 seconds (Boer and Hildreth, 1999; Underwood et al., 2002). Depending on the environment, the focus may be a leading vehicle or vehicles, a distant tangent point, or other obstacle or piece of physical infrastructure. A driver will make a mental world model of their environment, which is aligned to a driver's situational awareness, and allows them to anticipate future events. Up to this point, anticipation is very aligned with the broader definition as previously described. In regard to the two types of anticipation: strong and weak, we firstly need to consider the aspect of vehicle control. Michon (1985) defined three levels of control, namely strategic (trip planning), tactical (manoeuvre planning) and operational (vehicle operation). Weak anticipation involves a conscious decision process and the broader environment, which we may more readily find in regard to tactical control. An example may be the decision to change lane. Operational control on the other hand is more readily aligned to operational control, such as the performance of direct operational actions without direct forethought and necessary explicit decision making, such as steering or pedal use. The extent to which anticipation is strong or weak depends on the type of events, driver tasks, and the current environment.

A driver experiences various cognitive tasks while driving. The main driving task can be considered as a single task or a set of sub-tasks, such a longitudinal driving and lateral driving for example. Often a driver will face secondary tasks, which will place a further demand on their workload. Much research has been performed on the effects of secondary tasks, with some work also involving the role that anticipation plays. The vast majority of this relates to weak anticipation, as this is influenced by secondary tasks that can lead to a decrease in situation awareness and driving performance, e.g. due to distraction from additional tasks (Lee et al., 2001; Zheng, Tai, and McConkie, 2003). Often drivers can make deliberate decisions whether to undertake a secondary task given their situation, which has been described as a “deciding to be distracted” approach (Lerner and Boyd, 2005). These decisions are based on expectations about the future development of a situation and if the expected demands allow the execution of another task concurrent with the driving task (Schömig, Metz, and Krüger, 2011). The future development of the situation may be a continuation of the current state, in which inertia may play a role, or may be an expected change in the circumstances. The anticipative processes before starting a secondary task are crucial for proper control of the situation development during the interaction with the task (Schömig, Metz, and Krüger, 2011). An example of this may be a driver who chooses to delay a conversation with a passenger while performing a certain task. From this, it is clear that these processes relate to deliberate cognitive effort that can influence a driver's ability to anticipate and that we are clearly considering weak anticipation here. Distraction can also be caused by uncontrolled processes of events. Muhrer and Vollrath (2011) state that the effects of different distraction conditions on higher cognitive processes remain mostly unclear. It is known that distractions can influence the anticipation of events in a car-following scenario (Muhrer and Vollrath, 2011). Anticipation is required to know what will happen next, and to react adequately to the situation. Examples of the role of anticipation in this regard are drivers that may increase the distance to a leading vehicle (Ishida and Matsuura, 2001; Regan, Lee, and Young, 2008), may reduce speed (Horberry et al., 2006; Jamson and Merat 2005; Muhrer and Vollrath, 2011; Regan, Lee, and Young, 2008) or perform fewer lane changes (Beede and Kass, 2006) as a compensatory measure. It was also found that impairment of perception due to the visual distraction leads to a slower reaction as compared to a cognitive distraction. Overall, cognitive distraction negatively influences the anticipation of possible future actions of other car drivers while visual distraction deteriorates perception and thus the reaction to critical events. Therefore anticipation acts as a way of compensating for potential threats and possible high cognitive load, but in itself can also be negatively influenced by high cognitive workload, especially in the case of weak anticipation. Anticipation relies heavily on the ability to perceive the environment and therefore is also influenced by situation awareness. This requires a driver to constantly scan their environment, which is often performed by short glances (Underwood et al., 2002). In regard to strong anticipation, very limited research has been performed when applied to driving, mainly due to the more abstract character of the sub-conscious process. Nevertheless, there is sufficient evidence from general psychological and behavioural literature and of general anticipation in driving behaviour literature, to deduce a hypothesis of strong anticipation for driving.

3. Anticipation Reliance: Conceptual framework and theoretical underpinnings

In this section, we first extend the modelling and simulation framework introduced in van Lint and Calvert (2018). We then highlight the role of anticipation for task demand in this framework and present a new concept termed Anticipation Reliance (AR) that clarifies and describes important elements of the workload process of drivers. We conclude this section

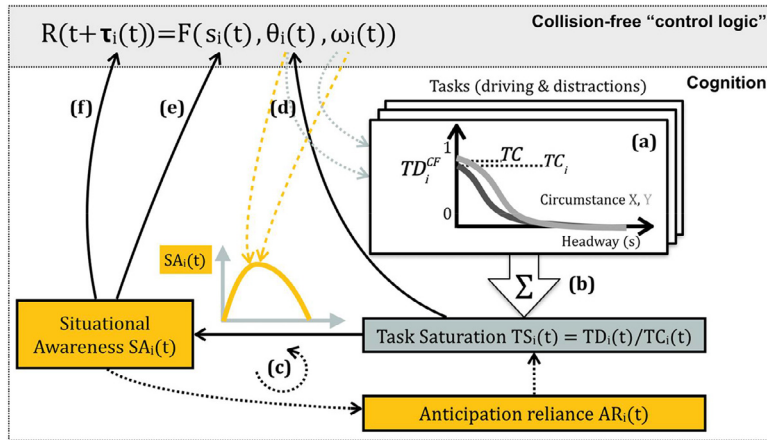


Fig. 4. Conceptual modelling & simulation framework with Anticipation Reliance.

with a short demonstrative example of the concept. In the section hereafter we explore a more elaborate simulation example to underpin the methodological contribution.

3.1. Simulation framework

In van Lint and Calvert (2018) we proposed a multi-level modelling and simulation framework that offers plausible endogenous mechanisms for perception error and reaction time dynamics and for response (e.g. desired speed) adaptation. The framework was demonstrated for the car-following task. In this paper we extend it to include anticipation and perception of drivers in a complex multi-lane driving environment. This extended framework is schematically outlined in Fig. 4.

The idea of the multi-level simulation framework in Fig. 4 is that it separates collision-free driving logic from the underlying cognition (perception, anticipation, decision making) that may affect this logic. The (reasonable) assumption underlying this idea is that all drivers share an objective to avoid collisions (in their car following and lane change behavior)—aside from maintaining other objectives such as minimizing delays or avoidance of getting stuck behind a truck. As a result, all drivers will try to compute a response $R(t)$ (acceleration, decision to change lanes, etc), as a function $F(t)$ of the perceived stimuli $s_i(t)$ (gaps, speed differences); their personal traits $\theta_i(t)$ (desired speed, degree of politeness, etc); and the environment $\omega_i(t)$ (traffic conditions, information and control) that is *collision-free in principle*.

However, the response mechanism $F(t)$ may not reach its collision-free objective due to limitations in a drivers' cognition. More precisely, poor situational awareness in terms of perception, comprehension and prediction (see Fig. 1) and/or other flaws in a drivers' cognition (e.g. risk taking, being distracted) may dynamically affect reaction time $\tau_i(t)$ and/or driver traits $\theta_i(t)$ (e.g. sensitivity to stimuli) such that the control law $F(t)$ temporarily deviates from its stable region. By stable region, we refer to the space of responses within which the control objective(s) can still be reached. In the worst case, collisions may occur. Our concept for modelling these destabilizing cognitions is by explicitly keeping track of the driver- and task-specific information processing resources $TD_i^q(t)$ that a driver uses to execute tasks (Fig. 4a). These tasks may be related to driving (car following, gap assessment) or to distractions (a telephone call). In van Lint and Calvert (2018) we propose the so-called "fundamental diagram of task demand" (FDTD) for car following, that makes it possible to differentiate between skilled or novice drivers by setting their respective task capacities $TC_i(t)$. The central hypothesis of our framework is that driver traits and circumstance-specific FDTD's can be formulated for *all* (or a selection of the most relevant) driving tasks (e.g. overtaking, weaving, responding to signalling, etc.). Total task demand $TD(t) = \sum_a TD_i^q(t)$ then describes the cumulative workload a driver is subjected to at any given moment; and task saturation

$$TS_i(t) = TD_i(t)/TC_i(t) \quad (1)$$

describes the degree in which this workload "saturates" the drivers' capability to safely drive (Fig. 4(b)). In case $TS_i(t)$ is larger than some threshold value, this may lead to a deterioration of awareness (Fig. 4c,e,f); and it may also trigger behavioral responses (Fig. 4d) in line with Fullers' Task Capability Interface Model (Fuller, 2011), for example in the form of reducing desired speeds or relaxing lane change desires.

The new idea we explore in this paper is that whereas task saturation may affect awareness, the inverse may also be true (Fig. 4c), that is, drivers may rely on their anticipation capabilities for one task (say car following), while executing other tasks (e.g. scanning for gaps to merge into, interpreting traffic signs, or even typing in an address in their navigation system). Clearly, the efficacy of anticipation reliance for safe and efficient driving depends on the quality of such anticipation. In the remainder of this section we offer the description of anticipation reliance and the cognitive compensative role it can play in driving.

3.2. Role of anticipation for task demand and assumptions

In our previous work and that of other authors, simplifications were made stating that demand from secondary tasks could cumulatively be aggregated to the primary task demand to form the total task demand (Mitropoulos and Nambodiri, 2010). Others have presumed the total task demand to be part of a single overarching task and therefore only consider a single task with multiple sub-tasks avoiding task accumulation (Muhrer and Vollrath, 2011; Salvucci and Macuga, 2002; Schömig, Metz, and Krüger, 2011). However, both of these approaches are simplifications that work in practice, but detract from reality and become more problematic when considering the interactions of multiple (sub-) tasks in co-existence. Also, the tasks related to lateral driving (lateral position in lane, lane change manoeuvres, etc) and longitudinal driving (i.e. car-following) are not cumulative and should be seen as two intertwined tasks or sub-tasks of the same driving task. This can also be well reasoned from a cognitive psychological point of view: performing a task requires perception, comprehension and cognitive processing. Performing additional tasks places a demand on the same processes, therefore requiring additional task capacity or reduced performance of one of the tasks. We are aware of the principle of induced task capability that states that the task capability can increase under a greater task demand (de Waard, Kruizinga, and Brookhuis, 2008; Liu and Lee, 2006; Verwey, 2000), however in relative terms, the task saturation (as described in Section 3) will still show an increase. It can be argued that the reduced performance of a task when performing multiple tasks can be compensated by sub-conscious processes that require much less task demand. We argue that this reduced sub-conscious process can exist for a large part due to the ability of a driver to (sub-consciously) anticipate future world states. Anticipation can be described as a (partially) sub-conscious process that means that any process to which it is applied, receives a reduction in task demand as sub-conscious processes require much less task demand than conscious cognitive processes. Clearly, this comes at the expense of some increased risk. However, given the goal of the additional task the overall risk is minimized.

We will clarify this line of thought with a simple example. Take a driver who is car-following, but is also trying to change lane. The driver is viewing various options in the adjacent lane looking for a gap. This is part of the 'lateral' task and is performed actively (i.e. with eye movements and cognitive processing of gap information). During this time, the driver continues to follow the leading vehicle, however is not as consciously involved with the longitudinal task. This is because of limited task resources or capacity. Instead, the driver takes a snap-shot of the current longitudinal situation and anticipates that little will change for a certain (short) period of time (e.g. 0.5 seconds). The anticipation of the longitudinal situation is a 'forecasted time-period of safety'. This anticipation is also dependant on the driver's experience and current state that allows them to make such a forecast. Therefore, anticipation is directly related to trust (or confidence) in that forecast. These principles are further elaborated in this section.

3.3. Overall concept: trade-off between perception and anticipation

Following the premise that anticipation, in combination with a certain degree of reliance, acts as a cognitive 'buffer' that allows a human driver to perform multiple tasks while sustaining a reasonable total task demand, we describe the role of anticipation in regard to task demand. To do this, it is necessary to define a quantity that encompasses this role of anticipation. Therefore, we introduce 'Anticipation Reliance' (AR) and define this as a *forecasted time-period of safety with a specific level of trust/confidence in that forecast*. AR allows a driver to perform multiple tasks, while not experiencing an aggregated effect of the task demand of these tasks. To understand this, we start by highlighting the presence of *primary* and *auxiliary* tasks. A *primary task* is a task that uses a human's main cognitive effort at a specific time (Horberry et al., 2006; Wong and Huang, 2009). Such a time period may be long or small, e.g. milliseconds such as a glance. By definition, all other tasks at that specific moment in time are defined as *auxiliary tasks*, which can be (partially) sub-consciously processed, but do not demand the main immediate cognitive load at a given time. Therefore, a human is able to perform multiple tasks at the same time, but only ever one primary task (Cantin et al., 2009; Lansdown, Brook-Carter, and Kersloot, 2004; Strayer and Drew, 2004). Nevertheless, these auxiliary tasks can be performed even without momentary conscious awareness and without placing the full task demand of the task on a human's task workload. Our hypothesis is that a sub-conscious reliance in regard to the perception of a specific task allows a human to process the task through anticipation and with a reduction in task demand for that specific task. Anticipation refers to a forecast of future states, which when combined with a degree of confidence of that state, we define as AR.

The effect of AR to reduce the task demand for the auxiliary tasks works by applying a reduction in task demand for that specific task though reliance on anticipation. This is graphically shown in Fig. 5. Say, there are two tasks with their own task demands: a primary task and an auxiliary task. The full task demand of the primary task places a demand on the driver. Due to AR, a reduction in the task demand of the auxiliary task can be applied. This leads to a total task demand at a set time that is lower than if both task demands would be aggregated. This process is described in greater detail in the following sub-section.

A graphical representation of the main related features is given in Fig. 6 and is further explained. The environment of a driver and their current state and traits directly influences the categorisation of Task Importance (TI). This is easy to understand, as a driver will react to their environment using their ability (i.e. traits and current state). For example, if traffic is busy and a driver is in a rush, there is a high likelihood that they will activate their lane change task. Another example, a tired driver may have very little interest in changing lane due to the required physical and mental effort. The presence of TI designates what a primary and an auxiliary task is. For the auxiliary tasks, Operational AR will be present. This is

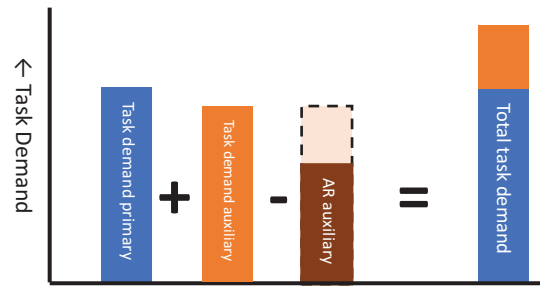


Fig. 5. Accumulation of tasks demand and AR (Anticipation Reliance) to make up total task demand.

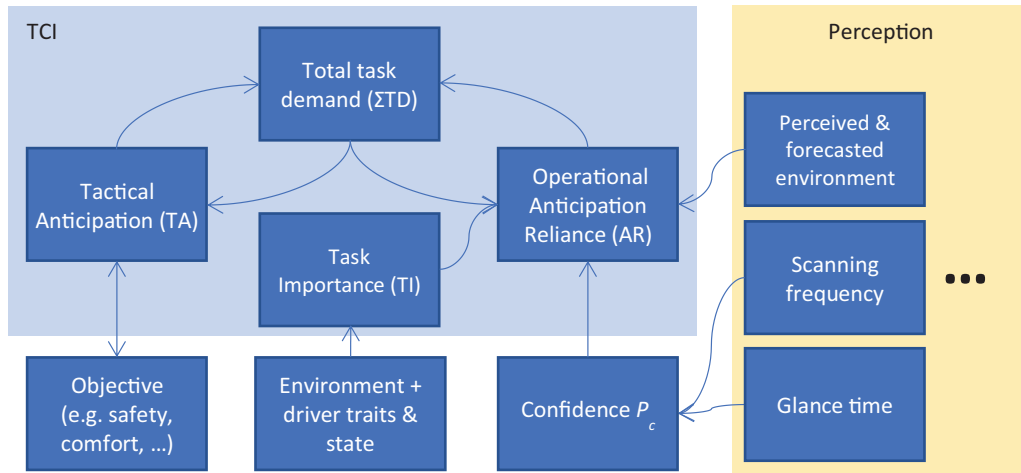


Fig. 6. Relational overview of Anticipation Reliance within the TCI.

'operational' as we are considering the performance of driving operations. For the remainder of the paper we will refer to this as just AR. AR allows the net resulting task demand, after subtraction of AR, of the auxiliary task to be calculated and consequentially the total task demand. The level of AR is influenced by a number of factors that relate to the quality of the anticipation and the confidence in it. Perception is a key aspect of the quality, i.e. how well can a driver perceive the environment relating to a certain task, but also, what is for example the scanning frequency and glance time in regard to a task? (Salvucci and Macuga, 2002) Within this framework, we limit ourselves to stating that perception quality and anticipation confidence is relevant, without further explicitly stating how these are determined (we are also aware that perception goes further than what we show in the Figure, but that is out of our scope). A final comment in regard to Fig. 6 is made for the presence of Tactical Anticipation (TA).

Within the framework, we do not make explicit use of TA, however we feel it is important to highlight the distinction between TA and AR to promote greater clarity. With TA, we refer to anticipation of a driver to their surroundings in a conscious cognitive fashion, such that conscious decisions can be made. This is the type of anticipation that we referred to as weak anticipation in Section 2 based on literature. This is contrary to anticipation within AR that is a sub-conscious process performed in a much shorter time span (often less than a second in time), which aligns to the previously presented strong anticipation. We give an example of TA in practice: a driver may make a conscious decision to leave a larger gap to a leading vehicle if they cannot see past the leading vehicle and therefore cannot anticipate (re: tactically anticipate) braking manoeuvres from vehicles up ahead by observing brake-lights. This follows the principles of the Task-Capability-Interface (TCI) model (Fuller, 2011).

3.4. Mathematical conceptualization of Anticipation Reliance

3.4.1. Task demand for lateral-longitudinal driving with anticipation

Following the premise that anticipation, in combination with a certain degree of reliance, acts as a cognitive 'buffer' that allows a human driver to perform multiple tasks while sustaining a reasonable total task demand, we describe the role of anticipation in regard to task demand. To do this, it is necessary to define a quantity that encompasses this role of anticipation. Therefore, we define 'Anticipation Reliance' (AR) as a *forecasted time-period of safety with a specific level of*

trust/confidence in that forecast, denoted by:

$$AR = A(h) * P_c \quad (2)$$

Here, $A(h)$ is the anticipated safety for ‘potential cognitive unloading’ as a function of a specific variable, e.g. h (headway) for car-following. P_c is the confidence of the anticipation, given as a perceived probability.

The AR acts as a ‘buffer’ to reduce the TD for a specific task when anticipation is applied to that task. In such a way, the total task demand can be rewritten as:

$$\Sigma TD_i(t) = \sum_a TD_i^a(t) - \sum_a AR_i^a(t) \quad (3)$$

AR is expressed in ‘amount of task demand’, which is unitless for both TD and AR . If applied to a driving system considering only lane-changing (lateral) and car-following (longitudinal) tasks, then the total task demand would be:

$$\Sigma TD_i(t) = TD_{CF} + TD_{LC} - \sum_a AR_i^a(t) \quad (4)$$

From this it is clear that when both longitudinal and lateral tasks are present, the total task demand will not be the sum of both, but reduced with the AR_i^a due to anticipation of the human driver of the tasks on which they are not mainly focused on.

Obviously there is a clear correlation between the values of AR_i^a and those of TD_i^a . We state that anticipation is predominantly applied to auxiliary tasks, e.g. tasks that are not the main focus of a driver at a time t , therefore a simplification is made that the TD_i^a of the main task is not reduced heavily by AR_i^a and that AR_i^a only applies to auxiliary tasks. When a driver is only car-following, the longitudinal task is the main task and lateral tasks become the auxiliary task for which anticipation is present. Anticipation in this case could be that no lane changes are expected from a driver’s own or other vehicles. When lane-changing or preparing a lane-change, the lateral task is the predominate task and the car-following task becomes the auxiliary task (albeit an important one), therefore a certain amount of anticipation is required in regard to a forecast of the traffic situation ahead of the vehicle for the coming (short) time period. To demonstrate driver deficiency in regard to Eq. (4): If a driver is not able to make a good estimate (affecting $A(h)$); maybe because of heterogeneous traffic speeds) or does not sufficiently trust their estimate (affecting P_c ; maybe because of insufficient driving experience or some sort of impairment), then the AR_i^a value of the longitudinal task will be lower and the TD_{CF} will retain a large influence on the total task demand (see Eq. (4)), possibly leading to task oversaturation and reduced driving performance.

Using anticipation in such a way, is to capture the reliance that a driver places on anticipation to allow them to reduce their overall total task demand. As well as aligning with the output of action from the cognitive process of a driver, it also logically complements a human’s physical restrictions in not being able to actively engage in too many active tasks at the same time. A driver is unable to look at a vehicle ahead of them and in their rear-view mirror simultaneously. Therefore, a degree of anticipation is required due to physical restrictions as well as cognitive ones, which this approach captures. We previously stated that anticipation is mainly required for auxiliary tasks, however this is not exclusive and anticipation can just as easily be applied to predominate tasks to further improve driving performance. An example of this is the ability of a driver to view multiple vehicles ahead to anticipate how their leading vehicle may act. However, AR also relies on how well anticipation can be performed. Using this example, when being able to look a few vehicles ahead, the confidence of a forecasted anticipation P_c is larger; the driver is confident about the anticipation and can (and is willing to) rely on it. When closely following a truck that obscures the view, $A(h)$ may be based on the anticipation that the truck will keep a constant speed. Hence, $A(h)$ is not small. However, as traffic ahead is not visible, P_c is low. As a result the car-following task demand cannot be reduced much by AR.

3.4.2. Simple demonstrative example of Anticipation Reliance

A simple quantitative illustrative example is now given of AR to enhance clarity. Say, a driver is on a dual lane road and wishes to change lane in dense traffic. Initially the driver will have a single task, namely that of car-following. When the driver’s lane change desire is activated, a second task can be defined, namely the lateral lane change task. The TD and AR for the car-following, lane change and total TD are shown in Fig. 7a-c. From this it is clear that the lane change desire, and consequently lane change task, is activated at time-step 1280. The time-step size here is 0.1 seconds. The driver is setup to check for a gap every 2 seconds, which involves a quick glance (0.2 seconds). When viewing the lane change task in Fig. 7b, initially the AR is high as the driver is focused on car following, but at certain intervals the lane-change task becomes the primary task as the driver glances to find potential gaps, i.e. cognitive perception is transferred to the lane change task. AR is not present during the time that the lane change task is primary. AR for the car following task is however present when the lane change task is the primary task (see Fig. 7a). Note, that the magnitude of AR for the car following task is not as high in relative terms as the AR is for the lane change task. This has to do with the criticality of a task. Failure to properly carry out the car following task is more critical than the lane change task prior to a lane change. Fig. 7c shows that the total TD is higher during this process of trying to lane change, but is certainly not the aggregate of the car following and lane change TD’s. At a certain time-step 1540, the driver stops searching for a gap and the lane change task is deactivated.

In this example, we considered the switching between tasks from a small time interval and allowed the primary and auxiliary tasks to switch in short succession. While this is more likely to be the way the mind works, we propose that

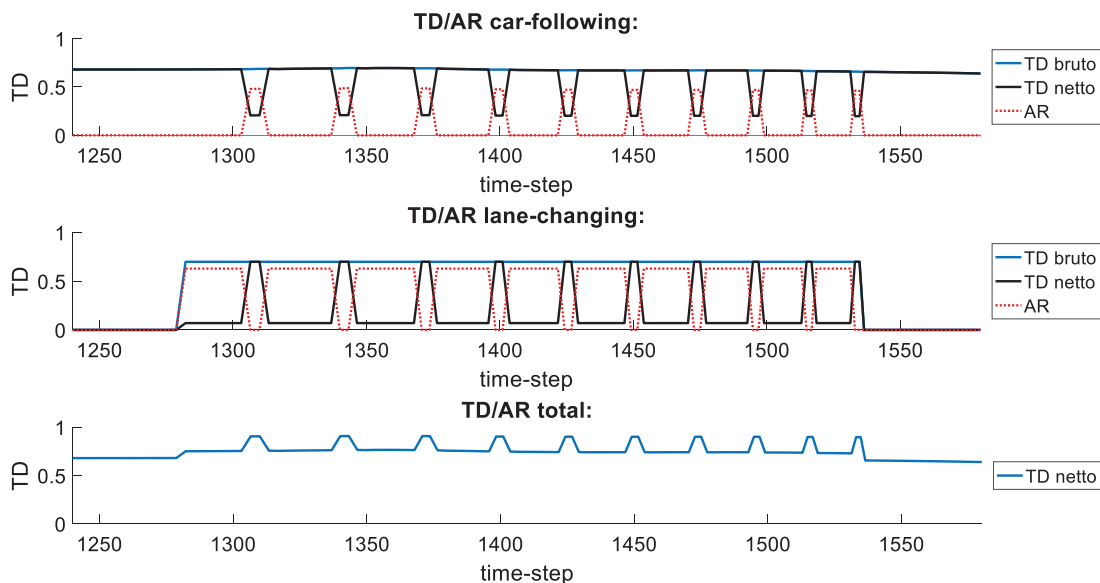


Fig. 7. Task Demands and Anticipation Reliance for a theoretical lane-change case.

when applied, it makes more sense to consider an average or critical distribution of the tasks during such a period. This would entail stating which portion of the time which task is primary and smoothing the tasks demands over this time period. This avoids implementing an unrealistic and unverifiable scanning frequency and allows the implementation in the model to be made easier.

4. Implementation of Anticipation Reliance and demonstrative case

4.1. Implementation of Anticipation Reliance for traffic simulation

This section describes the mathematical implementation of Anticipation Reliance for simulation. We first present the base model without human factors. We also briefly discuss an extension of the base model based on driving strategies, which underpins the consideration of driver awareness and perception. The base model and strategies are based on previous work. The strategies are interesting from a safety perspective as they induce a wider distribution of headways aligning better to reality, including smaller headways, and as they increase the number of lane changes to realistic levels. After that the model to incorporate human factors in to the perception is explained in detail.

4.1.1. Base model

For the base model, we use the Lane change Model with Relaxation and Synchronization (LMRS) (Schakel, Knoop, and van Arem, 2012), extended with driving strategies. This combination shows good resemblance of real traffic at both macroscopic and mesoscopic traffic flow characteristics. The LMRS has been shown to resemble overall congestion patterns, including capacity and saturation flow. Distribution of traffic over lanes is also resembled, as well as the average speeds on different lanes, for different densities and locations. The driving strategies add realism mainly on the mesoscopic level, with realistic headway distributions and an increased number of lane changes. These mesoscopic characteristics are important regarding our analysis, as distributed headways mean a presence of shorter headways, and an increase in the number of lane changes increases the number of disturbances. We briefly discuss the resulting base model here. For further details and underpinning of the base model, the reader is referred to (Schakel, Knoop, and van Arem, 2012).

The main concept of the LMRS is lane change desire which stems from a number of lane change incentives, and results in various behaviours depending on the lane change desire extent. Lane change desire is given by Eq. (5), where d is lane change desire (we omit detailing to which lane, left or right), d_r is lane change desire regarding the route and infrastructure, d_s is desire regarding maintaining or gaining speed, and d_σ is desire to change lane in order to get out of the way for faster traffic. All these desires may be negative, and are normalized values. Finally, θ_v is the level by which voluntary incentives are included. This value reduces as d_r increases. It should be noted that for trucks Eq. (5) includes an additional voluntary lane change incentive that makes them only use the right-most two lanes.

$$d = d_r + \theta_v(d_s + d_b + d_\sigma) \quad (5)$$

Four behaviours are defined based on the level of desire. For $d < d_{free}$, the desire is too small and no lane changes are performed. For $d_{free} \leq d < d_{sync}$, a lane change is only performed if it happens to be possible without preparation. For

$d_{sync} \leq d < d_{coop}$, the driver will adjust speed and position to the target lane (synchronization) in order to increase the chance of the adjacent gap to become acceptable. Finally, for $d_{coop} \leq d$ the follower in the target lane will cooperate and provide a gap. Both synchronization and cooperation are modelled as following the leader in the adjacent lane using the car-following model, but with a limited deceleration. Other behaviour that depends on the level of lane change desire is the gap-acceptance. The maximum tolerable deceleration from the car-following model to accept the gap is given by $d \cdot b$, where b is the maximum comfortable deceleration from the car-following model. Also, the applicable headway for gap-acceptance reduces as lane change desire increases, with a normal value of T_{max} and a minimum value of T_{min} . After the lane change, the car-following headway is relaxed back to T_{max} . This is known as the relaxation phenomenon (Laval and Leclercq, 2008).

The base car-following model we use is the IDM+ including extensions for the driving strategies. The formula is given in Eq. (6), where a is the maximum acceleration, b is the maximum comfortable deceleration, v_0 is the desired speed, s_0 is the stopping distance, T is the desired headway, and δ reflects a decrease in acceleration as speed increases, for which usually a value of 4 is used. The equation furthermore relies on the speed v , headway s and the speed difference with the leader Δv .

$$v' = a \cdot \min\left(1 - \left(\frac{v}{v_0}\right)^\delta, 1 - \left(\frac{s^*}{s}\right)^2\right) \quad (6)$$

$$s^* = s_0 + v \cdot T + \frac{v \cdot \Delta v}{2\sqrt{a \cdot b}} \quad (7)$$

The desired headway is dynamic and described with an endogenous phenomenon as given by Eq. (8). Here, T' is the headway as it results from relaxation, while ρ is the level of social pressure to the leader to increase speed or change lane to get out of the way. Social pressure depends on the desired speed, the speed of the leader, the proximity of the leader, and on the sensitivity of the driver to their own speed $\varepsilon = v_{gain}^{-1}$, where v_{gain} is a parameter from the LMRS. It describes the speed difference at which d_s is 1.

$$T = \min(T', \rho \cdot T_{min} + (1 - \rho) \cdot T_{max}) \quad (8)$$

As a response to social pressure of a follower, the desired speed is also dynamic and given in Eq. (9), where v_{max} is the maximum vehicle speed, f_{speed} is a compliance factor to the speed limit v_{lim} , and ρ^F is the perceived level of social pressure from the follower. Sensitivity to the social pressure is given by σ , while the absolute response is reduced as drivers are more sensitive to their own speed through ε .

$$v_0 = \min\left(v_{max}, f_{speed} \cdot v_{lim} + \frac{\sigma \rho^F}{\varepsilon}\right) \quad (9)$$

Lane change incentive d_σ is also a response to ρ^F , the strength of which depends on σ . This incentive also results in drivers delaying a lane change to let faster traffic pass by (momentary negative desire to change to the fast lane). As a result, the driving strategies allow much more realistic and lower values of v_{gain} relative to the LMRS without strategies. This then results roughly in a doubling of the number of lane changes, which is important for our analysis.

4.1.2. Perception of surrounding vehicles using anticipation reliance

In this section we describe the perception of surrounding vehicles, which is used as input for the model described in sections 3–4. The perception is mathematically described starting with the perceived and anticipated erroneous input for the model, and consecutively describing components of the equations with following equations. The actual implementation generally works the other way around. For clarity we first provide an overview of the implementation, including relevant equations. This also shows the overall information flow of the model.

Implementation procedure	Input	Equations
1. Task demand (TD _k) and anticipation reliance (AR _k) per task k	headway (h)*, desire (d)*	(18)-(21)
2. Task saturation (TS)	TD _k , AR _k	(17)
3. Situational awareness (SA)	TS	(16)
4. Reaction time (T _r)	SA	(15)
5. Perceived headway (s _e), perceived speed difference (Δv _e)	SA	(10)-(12)
6. Anticipated headway (s _p)*, anticipated speed difference (Δv _p)*	s _e , Δv _e , T _r	(13)-(14)
7. Compensation (T _{min} , T _{max})*	TS	(22)-(23)

* input from, output for, or parameters in the base model

Perception of surrounding vehicles is based on reaction time T_r and situational awareness SA , which has a maximum value of SA_{max} . If situational awareness is reduced, the error in perceived gap and relative speed increases. This error is included by a factor ξ as in Eq. (10), where i is the subject vehicle and j is the perceived vehicle. Gap $s_e^{ij}(t)$ at time t is perceived as $s_e^{ij}(t)$, and speed difference $\Delta v_e^{ij}(t) = v^i - v^j$ is perceived as $\Delta v_e^{ij}(t)$.

$$s_e^{ij}(t) = \xi(t) \cdot s^{ij}(t) \quad (10)$$

$$\Delta v_e^{ij}(t) = \xi(t) \cdot \Delta v^{ij}(t) \quad (11)$$

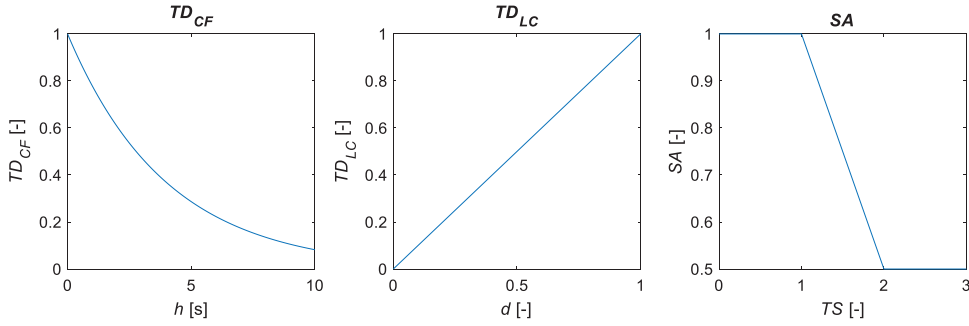


Fig. 8. Fundamental diagrams of task demand TD for car-following CF and lane changing LC , and the relation between task saturation TS and situational awareness SA .

The error factor ξ depends on the situational awareness SA as in Eq. (12). Here, γ determines whether the driver is overestimating, or underestimating. An example may be an underestimation ($\gamma = -1$) for 75% of drivers, and overestimation ($\gamma = 1$) for 25% of drivers.

$$\xi(t) = 1 + \gamma(SA_{max} - SA(t)) \quad (12)$$

The reaction time is incorporated by obtaining the gap and relative speed at time $t - T_r$. We assume that drivers compensate for their reaction time by anticipation using a constant-speed heuristic. This gives Eq. (13) for the final perceived distance s_p and speed difference Δv_p . Note that the perceived distance depends on the exact distance $\Delta s_i(t)$ the subject vehicle i has travelled between $t - T_r$ and t , and a perceived constant leader speed $v_e^j(t) = v^i(t) - \Delta v_e^{ij}(t)$. The perceived speed difference depends on the exact current speed of the subject vehicle i , and the perceived speed of the perceived vehicle j . These notions follow the assumption that drivers are well aware of their own actions during the reaction time. Finally, we have $\mu = 1$ for downstream vehicles, and $\mu = -1$ for upstream vehicles, as for upstream vehicles the gap is reduced when they are faster than the subject vehicle.

$$s_p^{ij}(t) = s_e^{ij}(t - T_r(t)) + \mu(v_e^j(t - T_r(t)) T_r(t) - \Delta s_i(t)) \quad (13)$$

$$\Delta v_p^{ij}(t) = v^j(t) - v_e^j(t - T_r(t)) \quad (14)$$

The reaction time T_r is related to the level of situational awareness through Eq. (15), where $T_{r,max}$ is the maximum reaction time. In case of perfect situational awareness, the reaction time is 0. Hence, T_r should not be interpreted as a physical reaction time, but as a reaction time over which significant anticipation errors may accumulate.

$$T_r(t) = T_{r,max}(SA_{max} - SA(t)) \quad (15)$$

Situational awareness is related to the task saturation TS as in Eq. (16) and as shown in Fig. 8c. Some deterioration of the situational awareness is assumed for levels above TS_{crit} . The maximum task saturation is TS_{max} above which no further deterioration of situational awareness is assumed. The level of situational awareness is then SA_{min} . We consider such levels of task saturation unreasonable for a realistic model, as drivers will prioritize or drop tasks. However, the values of TS_{max} and SA_{min} do determine the extent of deterioration of situational awareness.

$$SA(t) = \begin{cases} SA_{max}, & TS(t) < TS_{crit} \\ SA_{max} - (SA_{max} - SA_{min}) \frac{TS(t) - TS_{crit}}{TS_{max} - TS_{crit}}, & TS_{crit} \leq TS(t) < TS_{max} \\ SA_{min}, & TS(t) \geq TS_{max} \end{cases} \quad (16)$$

Task saturation is described as the extent to which total task demand saturates the available task capability TC . Total task demand is the summation of tasks k with task demand TD_k and anticipation reliance AR_k .

$$TS(t) = \frac{\sum_k (TD_k(t) - AR_k(t))}{TC} \quad (17)$$

The level of anticipation reliance present in each task is regulated on a priority basis. This is a dynamic process that depends on the level of task demand of each task. We will now first discuss the task demand for two tasks: car-following and lane-changing. These are shown in Fig. 8. We assume that at very small headways, e.g. when tailgating or just after merging in busy traffic, drivers are almost fully occupied with car-following. For larger headways, the task demand is lower. The task demand for car-following TD_{CF} is given in Eq. (18), where h is the time headway and h_{exp} describes the level of exponential decay of task demand as the headway increases. We employ an exponential decay as we assume that some demand is still present when headways are very large, while the demand is already quite low at headways two or three times the desired headway.

$$TD_{CF}(t) = e^{-h(t)/h_{exp}} \quad (18)$$

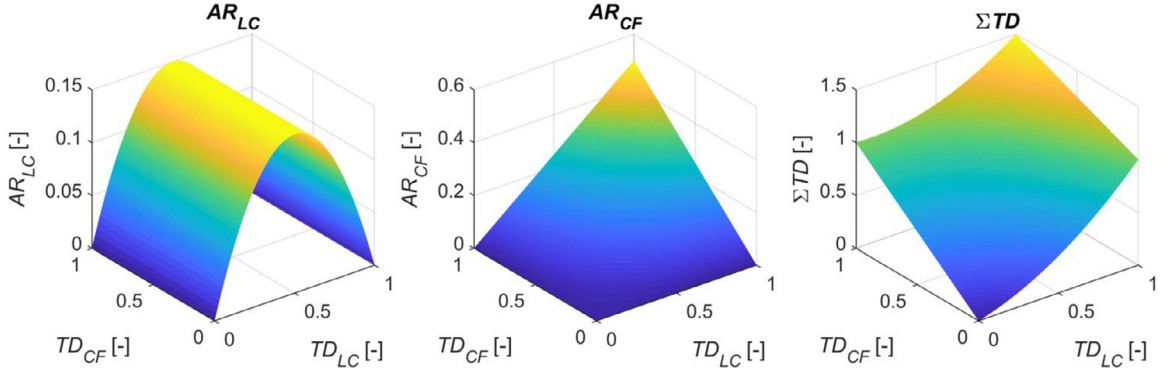


Fig. 9. Resulting anticipation reliance per task and total task demand resulting from the priority model.

For lane changing, we relate the task demand to lane change desire d , where negative desire is ignored.

$$TD_{LC}(t) = \max\left(0, \max_{z \in \{left, right\}} d_z\right) \quad (19)$$

Finally, the level of anticipation reliance per task is defined. This is a process of prioritizing for which drivers may have some set rules. We employ an approach with a primary task and auxiliary tasks (in our case one as there are two tasks in total). The primary task is prioritized, meaning that it will receive low anticipation reliance if the task demand is high, i.e. it obtains focus when required. If the primary task demand is lower, primary anticipation reliance is larger, though never larger than the primary task demand itself. This anticipation reliance in the primary task when it is not demanding, provides task capability to the auxiliary tasks should these be demanding. For lane-changing we assume that the maximum anticipation reliance that is acceptable is a fraction α of the task demand, while a fraction of β applies to car-following. We assume that lane-changing is always the primary task, i.e. if a lane change is highly desired and requires attention, it will receive attention and is the primary task. Priority for the primary task is given by $p(t)$, which we equate to the importance of lane changing, i.e. $p(t) = TD_{LC}(t)$. Eq. (21) shows these principles.

$$AR_{LC}(t) = \alpha \cdot TD_{LC}(t)(1 - p(t)) \quad (20)$$

$$AR_{CF}(t) = \beta \cdot TD_{CF}(t)p(t) \quad (21)$$

Fig. 9 shows the results of Eqs. (20) and (21) for combinations of TD_{LC} and TD_{CF} , with $\alpha = 0.6$ and $\beta = 0.5$. For the primary lane changing task it is clear that high levels of TD_{LC} are always accompanied by low levels of AR_{LC} . On the other hand, the car following task inhibits high levels of Anticipation Reliance for both increasing TD_{LC} and TD_{CF} . As a result, the total task demand may exceed a value of 1, but not excessively and only if both tasks are demanding.

In line with the Task-Capability-Interface model (Fuller, 2011) we implement a single mechanism to compensate task oversaturation. We assume that the primary method to alleviate task demand is increasing the headway, as lane changing is always assumed to be the primary task. In order to implement this we make T_{min} and T_{max} dynamic using Eqs. (22) and (23). The base values of these parameters are increased whenever $TS(t)$ is above TS_{crit} , by a scaling of β_T .

$$T_{min}(t) = T_{min} \cdot (1 + \max(0, \beta_T(TS(t) - TS_{crit}))) \quad (22)$$

$$T_{max}(t) = T_{max} \cdot (1 + \max(0, \beta_T(TS(t) - TS_{crit}))) \quad (23)$$

4.2. Case setup

We use the network as shown in Fig. 10 to demonstrate the application of the model in a case. This network induces mandatory lane changes near the lane-drop, as well as voluntary lane change in both lateral directions after the merge of

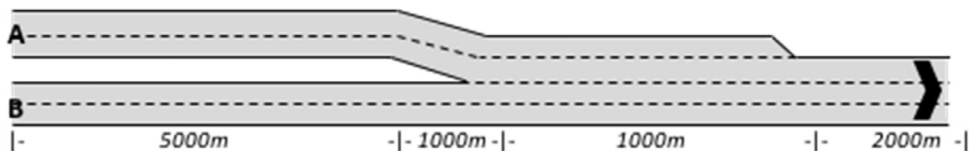


Fig. 10. Simulation network.

Table 1
Simulation parameters.

Symbol	Value		Description
	Cars	Trucks ^a	
a	1.25 m/s ²	0.4 m/s ²	Maximum acceleration
b	2.09 m/s ²		Maximum comfortable deceleration
T_{min}	0.56 s		Minimum time headway
T_{max}	1.2 s		Regular time headway
f_{speed}	$N(1.0308, 0.1)$	1.0	Speed limit adherence factor, normally distributed for cars
v_{max}	180 km/h	$N(85, 2.5)$ km/h	Maximum vehicle speed, normally distributed for trucks
σ	$T(0, 0.25, 1.0)$	1.0	Socio-speed sensitivity, with triangular distribution for cars
$v_{gain} (= \varepsilon^{-1})$	$LN(3.3789, 0.4)$	50 km/h	Speed gain at which d_s is 1, log-normally distributed for cars
SA_{min}	0.5		Minimum situational awareness
SA_{max}	1.0		Maximum situational awareness
TS_{crit}	1.0		Critical task saturation
TS_{max}	2.0		Maximum task saturation
TC	1.0		Task capability
$T_{r,max}$	2.0 s		Maximum reaction time at minimum situational awareness
α	0.6		Primary task fraction available for anticipation reliance
β	0.5		Auxiliary task fraction available for anticipation reliance
h_{exp}	4 s		Decay of car-following task demand for increasing headway
β_T	1.0		Headway increase scaling relative to task oversaturation

^a Only given when different from cars.

the two carriageways. The left and right carriageways have a maximum inflow of 3500 veh/h and 3200 veh/h respectively. During a warm-up period of six minutes, demand is at half this level, while demand rises to the full demand during the next 20 minutes, to remain high for 10 minutes and dropping to 0 at the simulation end which is one hour after the warm-up period. The truck fraction on both carriageways is 5%.

In order to evaluate our perception framework using AR, we use three different scenarios:

- Base; The base model using LMRS with driving strategies. (30 seeded runs)
- Task summation; The full model as described, but with zero anticipation reliance. (30 seeded runs)
- AR; The full model including anticipation reliance. (200 seeded runs)

Note that the task summation scenario is not expected to yield realistic results as the summation of tasks will yield unrealistically high total workload, which is precisely an aspect that AR addresses for multiple simultaneous driving tasks. Rather this scenario demonstrates why AR is required.

Table 1 shows the used parameters throughout these scenarios that are most important to our simulation study. Other parameters are set at default values as found in Schakel, Knoop, and van Arem (2012).

4.3. Performance indicators and hypotheses

The demonstrative case considers the driving performance of vehicles with their improved anticipation and perception through the described modelling approach presented in the previous sections. This is analysed on both a collective level through the consideration of the task saturation as a proxy for the cognitive load that drivers experience, as well as on an individual level. Arguably, the analysis of the variables on an individual level gives the greatest insights into the applied mechanisms and their validity.

For the collective analysis, distributions of the task saturation over all vehicles and over 30 runs per scenario are composed and normalized for easy comparison between each scenario. TS is measured for every vehicle at every time step, excluding the warm-up period as well as the first 3km and last 1km of the network. Furthermore, a distribution of the critical TS of the consecutive duration that vehicles are above the critical TS of 1.0 is comprised, over all vehicles and over 30 runs, excluding the warm-up period as well as the first 3km and last 1km of the network.

The number of accidents that occur throughout all simulation runs are also recorded, with simulations stopping when an accident occurs. This is used to derive a mileage per accident in each scenario. As the accident frequency in the AR scenario is low, it is run with 200 different seeds to derive mileage per accident (all other indicators are derived using 30 runs). The combination of the TS values over the vehicles and of the duration above a critical value gives an indication of the level of relative task load that is experienced by drivers and as a result also gives a general indication of their ability to perform their driving tasks, as a critical TS leads to a diminished SA and as a result potentially longer reaction times and diminished responsiveness of drivers. Consequentially, the longer a driver remains above a critical TS level, the greater the chance that accidents may occur.

In the case of task summation, without compensative awareness and strategies, one would expect critical traffic situations to lead to higher TS levels and for a longer period, as a driver is not able to as easily compensate their cognitive task capacity to avoid potentially dangerous situations. As a consequence, we would also expect a higher number of accidents due to this

limited ability to adjust behaviour in critical situations. As previously argued, task summation for multiple interacting tasks is not how humans deal with their task loads and therefore this illustrative scenario demonstrates the necessity to pursue alternative mechanism for dealing with these multiple tasks. In the AR scenario, this compensative mechanism is present. Therefore, we would expect the general level of TS to be lower than for the summative scenario, especially when the TS starts to, or exceeds, the critical TS level. A driver, at that point, would apply their AR to compensate against a task overload and be able to deal with the emergent traffic situations to a better extent, therefore potentially reducing the number of accidents that occur.

For individual driver-vehicles, we consider vehicles that have had accidents, to show the points at which the mechanisms are stretched to breaking point. In regard to the review of individual driver-vehicle performance, variables relating to the vehicle dynamics: acceleration a , and the vehicle speed, v , as well as the drivers cognitive state through: the individual and aggregated task demands TD and AR , the driver's reaction time T_r , and the drivers task saturation TS , are presented. Furthermore, the trajectory plot of the considered vehicle and the surrounding vehicles is shown in the lead up to the accident to give context. We will also show the TTC leading up to the accident as an often applied measure of traffic safety.

Finally, although the main focus for validation of the model is on aspects of traffic safety, as this aligns to human error and enjoys more attention from the traffic psychology domain, the effects on traffic flow phenomena may be equally demonstrated using the presented framework. However, demonstrating these based on cognitive constructs and as a function of task demands is more difficult, as these are generally not areas focussed on by traffic psychologists in their experiments and therefore would mean applying many more assumptions.

4.4. Case results

The case and its results are given to demonstrate the cognitive mechanisms that are modelled to give increased realism in traffic simulation. This is presented in two parts, the first considering the collective distributions of vehicles and their task saturation, as a proxy for drivers cognitive state. The second part focusses on the performance of individual vehicle-driver combinations and the microscopic mechanisms involved in the perception and awareness that lead to their driving dynamics.

4.4.1. Collective cognitive vehicle performance

We first consider the number of accidents that took place between vehicles over all simulation runs per scenario. A simple calculation based on statistics from the Netherlands Bureau of Statistics CBS (CBS, 2018a; CBS, 2018b), and the Netherlands Institute for Road Safety Research SWOV (SWOV, 2017), shows that on average one accident takes place for every 1.83 million¹ kilometers that are driven on motorways in The Netherlands, which gives us a ballpark Figure to compare against. The Netherlands has an above average safety record and in general motorways are also safer than other road types, therefore a fairer comparison might be made with a slightly lower value, however this is only meant as an indication of order of magnitude. In the base scenario, without driving tasks and AR, no accidents were observed. This is not surprising as the vehicles are basically driving according to the base vehicle model (IDM+ in our case), which is designed such that perfect knowledge is present and compensative breaking will always occur perfectly. During all base scenario runs, 691 thousand vehicle kilometers were driven without accidents. In the summative task scenario, an accident occurred for every 6.7 thousand vehicle kilometers driven. This is nearly a factor 200 more than what may be expected in practice, however is unsurprising as task summation unnaturally overloads driver workload leading to diminished driving performance. In the AR scenario, an average of 755 thousand vehicle kilometers was driven per accident, which certainly is in the same order of magnitude as the statistics we derived from practice. This average is based on six accidents during all 200 runs, which obviously is susceptible to large deviations if just a few more or few less accidents were to occur. Nevertheless, the general result would still be in the same order of magnitude, and while we make many assumptions in the model application, this would indicate that we are able to approach realistic levels of traffic safety.

The distributions of the task saturation, TS , and critical TS are shown in Figs. 11 and 12 respectively. This is shown for the summative task scenario and AR scenario, and not the base scenario as no task loads are considered in the base scenario. Firstly, the TS distributions show two figures that have similarities, but also some striking differences. There are three peaks present in both figures (Fig. 11a and b), which can be derived to three different driving states. The first is free driving, for which there is no car-following or lane changing, therefore the TS is very low, near to zero. The second is a state of car following in quieter traffic at a desired speed and distance, which shows up in the figures between $TS = 0.3-0.4$. The third peak that we can observe is near $TS=0.7$ for task summation and $TS=0.8$ for the AR scenario, and equates to a busy traffic state. Furthermore, we also see a fourth peak in the task summation scenario near $TS=1.1$ that is not present for the AR scenario. This peak is the result of dual car-following and lane-change tasks that are both active with workload compensation through AR. On the AR scenario, anticipation reliance acts as a workload compensating factor to allow a driver to perform both tasks without exceeding their task capability. In some extreme situations, drivers will still exceed $TS>1.0$ in the AR scenario, which also can happen in practice, however these are far fewer than when task workloads are

¹ Calculation based on data from 2017 for motorways in The Netherlands: 134393 Mkm driven in total on all road types (CBS, 2018b), multiplied by 45% as the share of all driven kilometers on motorways (CBS, 2018a), divided by 33032 accidents on motorways in The Netherlands (SWOV, 2017), gives 1.83 Mkm/accident.

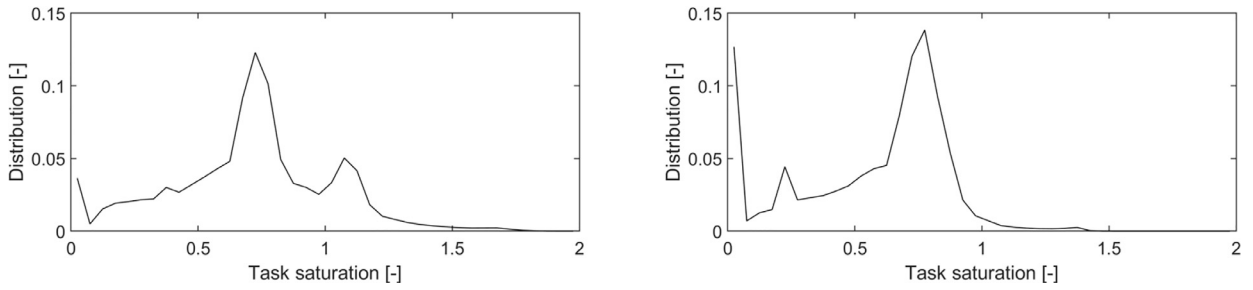


Fig. 11. Task Saturation distribution for a) task summation scenario, b) AR scenario.

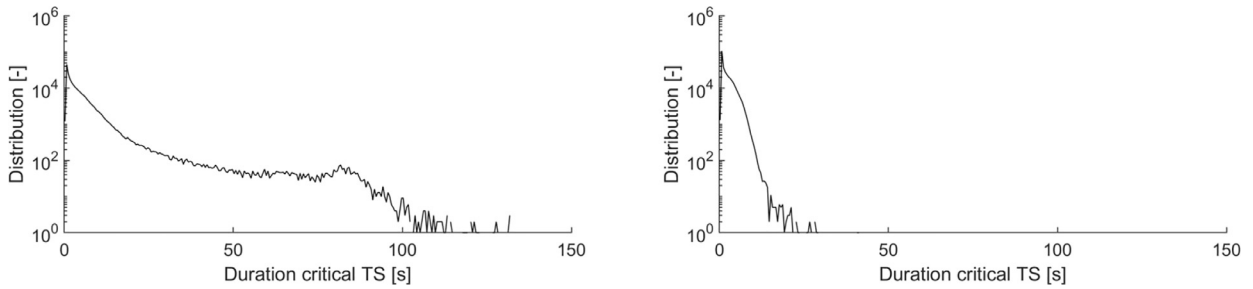


Fig. 12. Critical Task Saturation duration distribution for a) task summation scenario, b) AR scenario.

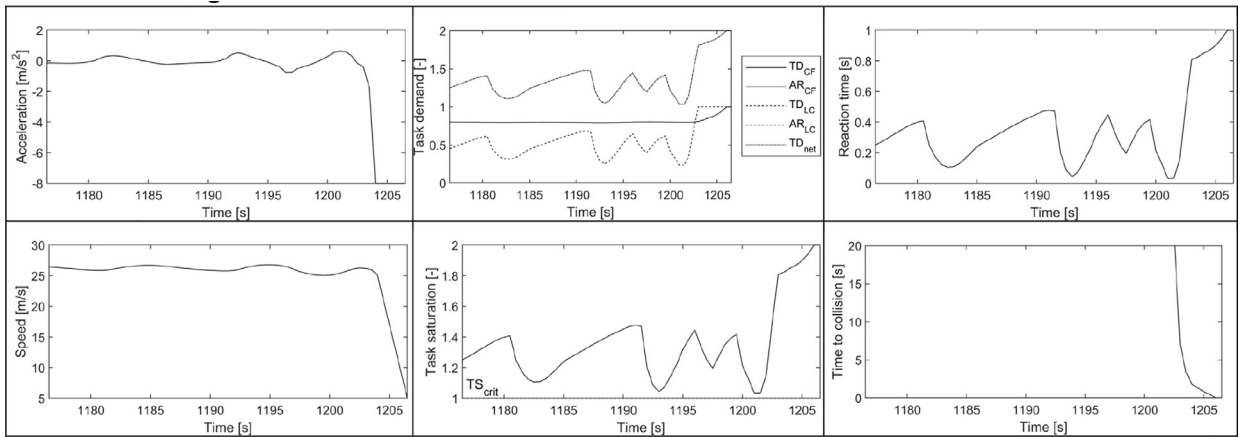


Fig. 13. Task summation scenario vehicle performance example (run #6).

aggregated. This same effect can be viewed in Fig. 12 for the critical task duration. The task summation scenario shows that drivers are operating above the critical TS for up to 100 seconds in some cases, which intuitively does not appear valid (note that no validation data exists to test this at present to the knowledge of the authors). The exceedance of the critical TS in the AR scenario occurs for 20 seconds at most and much shorter in most cases, with many fewer occurrences of TS exceedance.

4.4.2. Awareness mechanism for individual driver-vehicles

Viewing individual driver-vehicle data based on the scenarios further aids understanding and verification of the framework. A representative example of an accident from the task summation scenario is shown in Fig. 13, while two examples from the AR scenario are shown in Figs. 14 and 15. The trajectory plots of all six accidents from the AR scenario are also shown in Fig. 16.

From Fig. 13, it is clear how the TS value for this driver is above the critical threshold, as task demands TD_{CF} and TD_{LC} are both high in the lead-up to the vehicle crashing. Traffic is busy, which can be seen from the high TD_{CF} value, while

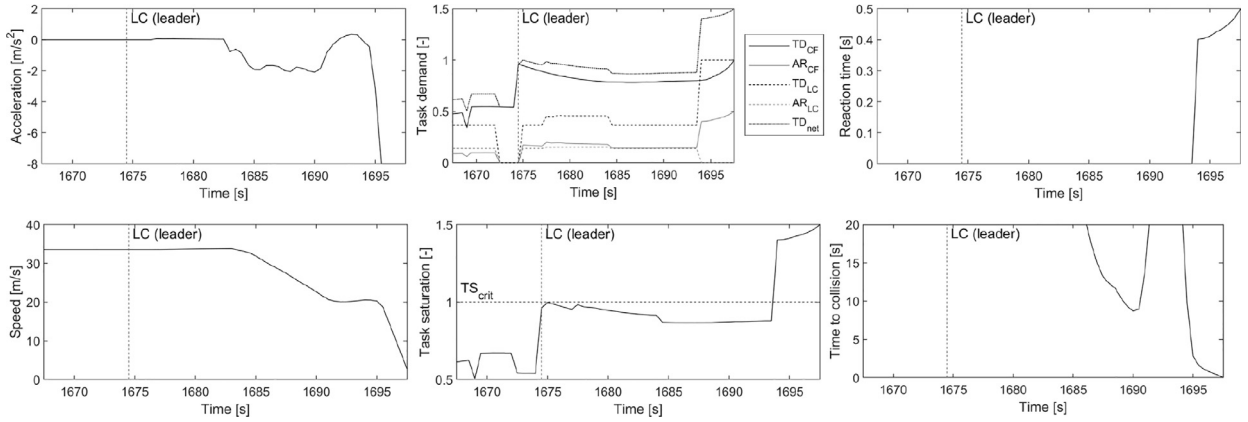


Fig. 14. Anticipation Reliance scenario vehicle performance example (run #133).

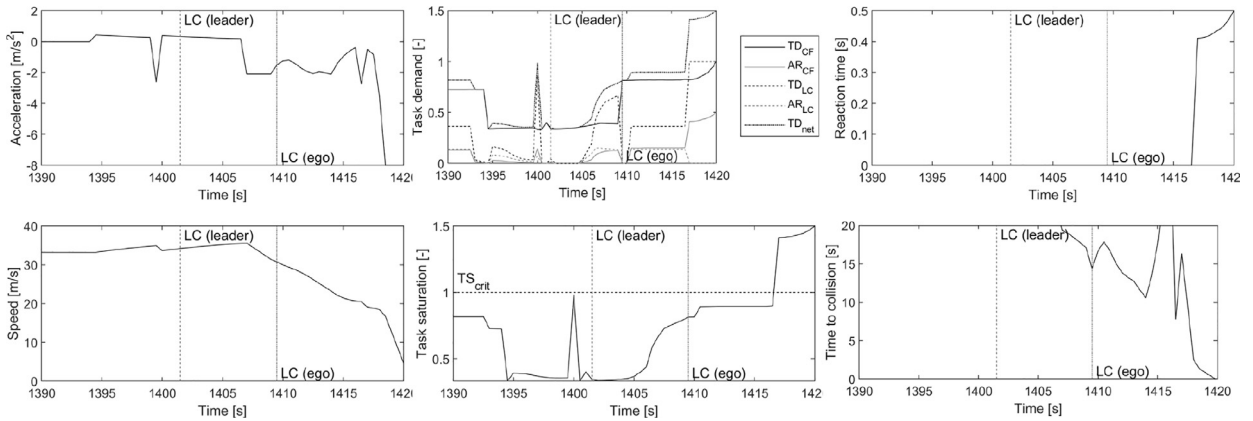


Fig. 15. Anticipation Reliance scenario vehicle performance example (run #168).

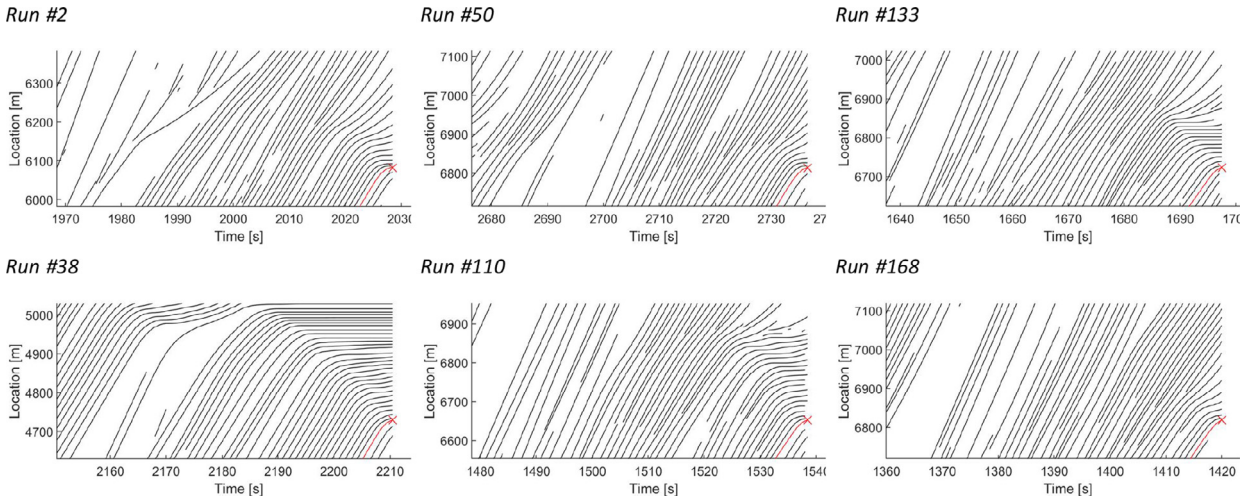


Fig. 16. Trajectory plots prior to vehicle accidents for the Anticipation Reliance scenarios.

the vehicle has a high desire to change lanes, which may be mandatory or due to the current traffic conditions. Due to the high and critical TS value, the cognitive reaction time² of the driver is affected and increases. At a certain point, the traffic

² Note that only the cognitive part of the reaction time is modelled. The total reaction time exists of the cognitive and physical reaction time, which has often been assumed to be in the vicinity of 1.0-1.5 seconds for an average attentive driver, but will often be in the range of 0.7-3 seconds across the driving population (McGehee, Mazzae, and Baldwin, 2000).

conditions coupled to the driver's current state and reaction time collude to lead to the driver not being able to react fast enough and the accident occurring.

For the two examples for the AR scenarios (Figs. 14 and 15), there are similarities to the summation example, but also very obvious differences leading up to the accidents. The main difference is the way that AR acts as cognitive compensation for the task demand. For run 133 (Fig. 14), we see a vehicle change lane in front of the ego vehicle at time 1674s. This immediately leads to a higher TD_{CF} due to the close proximity of the leader, but not enough that the ego driver feels the necessity to brake and increase the gap. The ego driver does gain a small TD_{LC} from an increased lane-change desire, which can be caused by the constrained driving. From the trajectory plot (Fig. Fig. 16), we can observe a strong congestion wave approaching the ego vehicle that causes the drivers ahead to perform a strong braking manoeuvre. At the point that the shockwave reaches the ego vehicle, it also decelerates sharply, but insufficiently. During the deceleration, a strong lane change desire also occurs, which can be viewed as an attempt to perform an evasive steering manoeuvre. This was not possible (either due to a lack of space or time) and the ego vehicle hits the vehicle in front with a relatively low speed (4m/s) due the attempt to avoid the crash by performing an emergency stop.

The second example, shown in Fig. 15 of run 168, shows that the ego vehicle initially has a low TS, while at a certain time (1402s) another vehicle changes lane in front of it with a lower speed. This means that the ego vehicle starts to catch the leading vehicle quickly and a lane change desire grows along with an increased TD_{LC} . The ego vehicle successfully changes lane at time 1409s closely behind another vehicle. From the trajectory plot (Fig. 16), we can see that this happened shortly before a new congestion wave occurred ahead of the ego vehicle. The ego driver was not able to decelerate and react in time to prevent a collision with its leader.

These examples demonstrate that while task combinations for drivers are captured in the framework in a more realistic fashion, accidents can still occur, which is very much in keeping with real driving performance. Moreover, this is captured by utilizing a driver's cognitive ability in close connection with the vehicle dynamics. This is further discussed in the following section.

5. Discussion on Anticipation, awareness and perception

In this section, we discuss aspects of anticipation, awareness and perception in relation to the proposed concept of Anticipation Reliance and what this means for traffic theory and simulation, as well as considering the role of other items that have become evident during the research.

As previously shown (van Lint and Calvert, 2018), vehicle dynamics can be captured and explained including their driver's psycho-cognitive abilities in a modelling framework. And while driving tasks were applied, the way multiple tasks are dealt with was not addressed due to the additional complexity that this gives. This was also not required in the original framework, as only longitudinal driving was considered without overtaking, hence only a single driving task was present. By arguing, based on relevant literature, that anticipation of human drivers plays a major role as a compensative factor when multiple tasks are applied, we have offered a scientifically sound and well positioned mechanism to address the difficulty of multiple driving tasks that is both implementable in simulation and is face valid based on current understanding and evaluation of vehicle driving performance. The presented case aided this by demonstrating the ability of the framework to model the described human factors processes with task demand and AR in a stable and verifiably valid manner. Both the individual analysis of drivers, as well as the effect of driver workload and traffic accident indications aligns with what we find in literature and can reasonably argue with the current quantitative knowledge on these aspects. This also showed why mere task summation cannot be presumed to be a valid approach and how the concept of AR does lead to realistic vehicle-driver mechanisms. The distinction between weak and strong anticipation to describe differences in anticipation allows a conscious and sub-conscious distinction to be made, with the latter implemented in the form of Anticipation Reliance to compensate cognitive workload when multiple cognitively conflicting tasks are undertaken. It quickly became apparent that we could not merely consider anticipation, but had to include a further aspect that corresponds to a driver's trust of their own perception. This aspect of 'Reliance' gives an indication of the quality of a driver's anticipation, which can be influenced by many different internal (e.g. driver cognitive state) and external (e.g. time) factors. Anticipation in itself is influenced by a driver's ability to observe and process information as we described in Section 2. Imperfect perception and cognitive processing can lead to a diminished level of anticipation, while time also plays a role, as infrequent updating of anticipation based on the latest state of the surrounding system can also lead to diminished anticipation. These aspects of the quality of the anticipation in time are addressed in the reliance part of AR. Within our further analysis in this paper, we have not analysed or applied the vast number of potential ways that anticipation can be negatively influenced. This goes beyond our intention to introduce the concept and dives deeper into cognitive psychology than we are willing to do at this phase of development. However, we would urge and encourage experts from these fields to align with this thought process and application to give further descriptions and details in this regard, preferably linked to strong empirical evidence. This is especially relevant for cognitive processes that are impaired through a driver's internal processes, such as intoxication or exhaustion, but certainly also the influence of external factors that will have an effect on cognition performance, such as environmental conditions. In our example case, cognitive performance was kept generic, but we would also encourage scholars to explicitly make links to specific cognitive impacts and evaluate their influence of driving behaviour through this framework. To model these processes, additional data collection will be required. Much of this will be from cognitive experiments under different

circumstances, from which a driver's level of task capacity and task demand will need to be captured, as well as aspects on the level of their situational awareness, and aspects that explicitly align to their anticipation (also see Fig. 6).

In the presented case, a base model with driving strategies was used as this provides a realistic headway distribution and number of lane changes. In particular the model creates platoons of vehicles following closely on the median lane as all but the platoon leaders have a desire to drive faster. In combination with the increased number of lane changes, this creates circumstances for critical deceleration waves. AR can arguably be implemented without these mesoscopic traffic features. However, quantifying the AR framework is no easy task as cognitive aspects cannot be directly measured. Hence, by optimizing the realism in the base model, the presented parameter values of the AR framework give a reasonable indication. Still, the values are determined for the chosen mental task regulator that for the purposes of this paper is a simple implementation. It can be argued that drivers make many more complex priority decisions, especially when they are experienced. This includes dropping tasks and priorities depending on estimated opportunities for tasks. For instance, for a non-mandatory, but highly desired lane change, the lateral task may receive low priority for some seconds as it is anticipated there will be no suitable gap, possibly missing a gap if the anticipation was faulty. The mental task regulator also provides a means for targeted task-saturation compensation. In the presented case, we only use compensation by increasing the headway. In reality there are many more options and it would make sense to apply most compensation on aspects involving tasks with high task demand and low anticipation reliance.

A major motivation to develop the original framework was to offer a balanced description of human driving behaviour when set against connected/cooperative automated vehicles (CAV). The introduction of mixed traffic of CAVs and human driven vehicles (HDV) will lead to shifts in SA and task demands, and consequentially in driver perception and awareness. This will especially be the case where a driver merely has a monitoring role and may easily become distracted (Calvert et al., 2019). But also for increased connectivity amongst vehicles, where in-car systems will play a role and may lead to additional tasks, even for HDV drivers (Muhrer and Vollrath, 2011). These are trends that require further investigation in the context of the presented framework. A first initial exploration has already been performed for transition of control (Calvert and van Arem, 2020), but so much more has still to be done.

A further finding from the analysis that we did not explicitly address during the results discussion was the use of Time-To-Collision (TTC) as an indicator for traffic safety. We found, as other authors have also previously mentioned (Archer, 2005; Mullakkal-Babu et al., 2017; Tageldin, Sayed, and Wang, 2015) that in many circumstances TTC lacks in descriptive power. This is due to the requirement that vehicles need to be approaching each other in space and time to allow a valid value for TTC to be given, while in traffic flow it is very common for vehicles to drive at close proximity with relatively small time gaps. These situations can in no way be described as safe, but in many cases will not offer a TTC value if the front vehicle moves with an identical or greater velocity to the following vehicle. In homogeneous traffic, such a situation would be fine, but traffic is rarely homogenous and the heterogeneity found between vehicles can and often does lead to a following vehicle not being able to react sufficiently to a strong braking manoeuvre of a leading vehicle, leading to a collision that is only observed by a TTC indicator in the final seconds before an accident (Figs. 13f and 14f demonstrate this well). Ideally, an indicator for safety should yield values also in the case of near-misses and situations in which an accident does not occur. For this reason, we would argue and urge the community to consider the development of a new measure for safety. We are aware of other more complex indicators, such as safety fields, post-encroachment time, time proximity, gap time, DRAC (Deceleration Rate to Avoid a Crash), etc. (Archer, 2005; Ma et al., 2011; Mullakkal-Babu et al., 2017; Tageldin, Sayed, and Wang, 2015) although many of these are often also TTC-based. And these often require a greater complexity of input and calibration (in some cases), while a generic indicator for safety is better suited with greater simplicity, which TTC does achieve, but with a diminished validity under many circumstances.

6. Conclusions

In this paper, the concept of Anticipation Reliance (AR) has been introduced in a multi-level modelling and simulation framework to describe the role of anticipation in human driving. Human factors lies at the heart of driving behaviour, but is rarely explicitly considered in simulation. AR is a breakthrough concept that is able to bridge the gap in modelling human driving behaviour through consideration of driver tasks for simulation, when multiple driving tasks are considered. In practice, a driver will also perform multiple tasks, therefore this breakthrough aligns with the situation in practice. When performing multiple tasks, it has been demonstrated that the task demands cannot be merely aggregated; it has been argued that AR can act as a compensative process that captures a drivers ability to anticipate for various traffic situations, and by doing so drivers do not need to fully consciously engage simultaneously with all driving tasks. This process therefore allows drivers to perform multiple driving tasks without becoming cognitively oversaturated through their tasks. This methodology is also demonstrated in a case that considers performing longitudinal driving tasks and lateral lane changing tasks. The case shows that the underlying mechanisms that are introduced are valid and reasonable, while the case also demonstrates the ability of the framework to capture real driver error and compensative mechanisms in driving, on a human factors and vehicle dynamics level that has not been seen previously in traffic modelling. Due to the complex and sometimes abstract understanding of deeper cognitive human process, including those in human driving, justifiable assumptions have been made. The authors invite the traffic research and especially the human factors communities to derive empirical evidence that can be used to further detail the presented framework and concepts and validate them where currently limited to no empirical evidence exists.

CRedit authorship contribution statement

Simeon C. Calvert: Conceptualization, Formal analysis, Methodology, Validation, Writing - original draft, Writing - review & editing. **Wouter J. Schakel:** Conceptualization, Formal analysis, Methodology, Software, Validation, Writing - original draft, Writing - review & editing. **J.W.C. van Lint:** Methodology, Writing - original draft, Writing - review & editing.

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Supplementary materials

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