DRIVER BEHAVIOUR MODEL

FOR THE

MULTI-AGENT REAL-TIME SIMULATION

MASTER THESIS

Neil E. Absil

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Driver Behaviour Model for the Multi-Agent Real-time Simulation

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MASTER THESIS

Driver Behaviour Model For the Multi-Agent Real-time Simulation

By
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Preface

This research was carried out at TNO Build Environment and Geosciences, within business unit Mobility and Logistics, under the supervision of Delft University of Technology, as part of a graduation project for a master in Computer Science.

Prior to this graduation project a literature study was carried out to become familiar with research relevant to traffic safety, modelling driver behaviour and associated simulation techniques. Forming a basis of domain specific knowledge necessary to understand traffic safety and ultimately implement a driver behaviour model in a micro-simulation environment. At the end of the literature study a conceptual model was created (Absil, 2008).

I would like to thank TNO, and specifically my supervisors Gerdien Klunder and prof. Ben Immers, for the opportunity to carry out this interesting research and for their support during the project. Additionally I would like to thank my supervisor from the Delft University of Technology, Leon Rothkrantz, for his guidance, practical tips and advice. I would also like thank Bart Netten for his assistance with MARS and his insights. Finally I would like to acknowledge Arshad Abdoelbasier whose work and well written thesis formed the starting point of my research and graduation project.

Abstract

This research focused on the modelling of realistic "human like" driving behaviour for the purpose of studying and understanding the complex interactions that lead to accidents. The ultimate goal of which is to develop a driver behaviour model that can be used in simulations to analyze and understand driving behaviour and human errors for the purpose of increasing road safety.

A rigid and practical psychological model was selected as the conceptual basis for a software model that was designed and implemented in a micro-simulation environment. The driver behaviour model extends the current simulation providing more realistic traffic and driving conditions in a flexible framework.

The research covers the areas of traffic safety, human factors engineering and psychology. Ultimately a driver model design will be developed and implemented in TNO's simulation environment MARS.

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List of Definitions

DBM	**D**river **B**ehaviour **M**odel
MARS	**M**ulti-**A**gent **R**eal-time **S**imulation, TNO's propriety micro-simulation environment
TNO	**T**oegepast **N**atuurwetenschappelijk **O**nderzoek, is a Dutch research institution, where this research was carried out.
UML	**U**nified **M**odelling **L**anguage, an object modelling and specification language used in software engineering
XML	E**X**tensible **M**arkup **L**anguage

Chapter

1

1. Introduction

In this chapter a brief introduction, background information, goals and the relevance of traffic safety research will be explained.

The Netherlands is one of the safest countries in the world to drive in, with approximately eight million people driving everyday and less than 800 traffic related fatalities per year. Still society has a vested interest in lowering the accident rate even further – the so called "vision zero" policy.

In the past accidents were viewed as a failure of the driver to react fast enough or correctly - leading to a focus on the perception-motor skills of the driver (Summala, 1988). As a result accident prevention initially focused on better training, safer cars and roads, with clearer signs so that the driver always knows what to expect. However the condition of the roads and other physical factors has reached a level where further improvements have a diminished influence on the number of accidents. TNO has recognised this theoretical barrier limiting further improvements and believes that new insights into improving traffic safety can be achieved by more accurate and realistic models and simulations.

90% of all accidents can be contributed to human errors, making the development of a driver behaviour model essential to any attempt to improve road safety through simulation. A wide array of research from traffic engineering, human factors engineering to psychology address these issues and attempt to model and explain the complex set of events and interactions that lead to accidents. Another reason to develop simulations (for the purpose of studying traffic safety) is the simple fact that fatal accidents rarely occur – and causing accidents to occur in real life for purposes of research is obviously not a viable option. Therefore many simulations have been developed to study the different aspects of traffic.

For these reasons TNO has initiated research into simulations focused on analyzing traffic safety in order to gain insight into the circumstance, behaviour and factors that lead to accidents, so that accidents can be prevented. Advanced driver assistance systems, adaptive cruise control and other new technologies designed to improve traffic safety can also be tested using these simulations.

TNO, industry and researchers quickly realized that a realistic driver decision model that could produce "human like" behaviour, causing human errors associated with driving, would be at the heart of any serious attempt to significantly improve traffic safety. This research was initially carried out by Arshad Abdoelbasier (Abdoelbasier, 2006) at TNO, with the goal of creating a driver behaviour model.

Historically, traffic simulations were modelled for highways, focusing on routing, congestion problems and increasing efficiency. TNO's simulation environment was no exception. As a result Abdoelbasier was required to first implement an intersection model (statistically this where the most accidents occur) and a vehicle model capable of correctly negotiating an intersection. These elements needed to be properly implemented before undertaking the development of a realistic driver behaviour model. Unfortunately, this left precious little time to create a driver behaviour model, which is inherently complicated. Although Abdoelbasier succeeded in implementing a rudimentary driver behaviour model, much work still remains and his research forms a basis for this research. Abdoelbasier observed (Abdoelbasier, 2005):

> *"This [the driver model] is arguably the most important part of the model, since all behavioural characteristics and simulated human decisions making processes reside here. These are commonly thought of as the most important contributors to safety in traffic, and because of their nondeterministic nature also the most complicated to emulate."*

The work done by Abdoelbasier is a starting point, which will be continued and extended in TNO's simulation framework.

1.1. Background information

TNO is a research institution that focuses on applied sciences and innovation in sectors ranging from defence to quality of life. Within the core area of 'Built Environment and Geosciences', business unit 'Mobility & Logistics' is concerned with the development of intelligent traffic systems, infrastructure and policy that will make travelling efficient, safe and sustainable.

To achieve these goals TNO is involved in ongoing research into traffic safety. The work conducted during this project will touch on some of areas of this ongoing research. This is a brief overview of the research currently being conducted related to this project.

- Continued development of TNO's micro simulation environment: MARS (Multi-Agent Real-time Simulation).
- Video capture and analysis of traffic.
- Gap acceptance model by Tim van Dijk, which is currently under development
- Abdoelbasier's research.
- Nina Schaap is conducting ongoing research into human factors, psychology and behaviour of drivers.

Aboelbasier's work focused on creation a realistic micro-simulation of intersections, in MARS, for the purpose of deriving safety indicators. To construct an intersection model for the micro-simulation three steps were recognized:

1. Implement the actual intersection model
2. Implementation of a vehicle model, with characteristic attributes of vehicles, such as breaking and turning circles.

3. Implementation of a driver behaviour model.

The final step was only implemented on at basic level.

1.2. Aim and motivation for this research

The main goal of this research is to expand the intersection micro-simulation, by Abdoelbasier, to include realistic "human like" behaviour. Formally the goal is:

> *To develop and implement a drive behaviour model (DBM) in the Multi-Agent Real-time Simulation, so that more realistic experiments can be carried out for the purpose of traffic safety analysis.*

In order to achieve this goal the key questions will have to be answered:

- Which psychological model is best suited for implementation into a traffic simulation?
- What are the key factors and behaviours that influence driving and safety?
- How will driver behaviour be transformed and integrated into the Multi-Agent Real-time Simulation?

A significant problem with traffic simulations is the fact that the vehicles drive in a homogenous fashion. The vehicles all drive in the same way and display identical behaviour, and also driving in a flawless, perfect way. Unfortunately this homogenous driving behaviour does mirror reality, and is a limiting factor in the study of traffic safety. Realistic driving simulations require some form of behaviour of the drivers, in a human like way, in order to make the simulation more realistic and accurate.

Since Abdoelbasier's intersection model was created in MARS and TNO has a vested interest in the continued development of this micro-simulation model, only this simulation environment was considered. Furthermore, the modularity and flexibility of MARS means that the current intersection model can be expanded to include human like behaviour.

1.3. Societal and scientific relevance

Statistically seen accidents are rare events, fatal accidents by comparison practically do not occur. In order to make roads even safer studying accidents is necessary to understand why they occurred. The inevitable paradox is that accidents occur so infrequently making accidents difficult to study. Carrying out accidents on purpose is not a viable option either. A far better solution would then be to create an artificial environment in which realistic accidents occur.

Human behaviour is an integral part of and major contributing factor to the events and decisions that lead to an accident. Any realistic simulation for purpose of studying traffic safety would need to incorporate some form of human behaviour model. This is one of the main motivations for TNO to develop a driver behaviour model. TNO is nearing the limit of what safety research can accomplish through improvements to the condition of the roads, better and clear information for the driver, etc. no longer greatly improve the safety of traffic. To further improve safety the human driver must be studied and understood. As well as how technologies such as adaptive cruise control (ACC) and advanced driver assistance system will interact and help the driver.

Besides the obvious academic interest of doing research in this field, lowering accidents and improving safety is of interest to everyone.

1.4. Expectations and constraints

Only vehicles such as cars and trucks will be considered in the simulation and models. Pedestrians and cyclists will be excluded in order to simplify the model. Once a proper and working model has been developed pedestrians and more complicated roads and intersections can still be added.

Although TNO has video footage, this data is from highways and has not been analyzed for purpose of studying safety. At some stage TNO plans to re-analyze this data focusing on safety but this will only happen in the distant future. New video footage, specifically for studying traffic safety, is in the making but will most likely not be completed and analyzed in time so as to be useful during this research. It is also questionable how useful such video footage would be, the age, gender and other characteristics still cannot be ascertained. A problem with data in general is that it is either too specific or too generic to be useful. For these reasons and time constraints no or limited calibration and validation of the model will be possible during this project.

In this research limited attention will be paid to complex emotions and the effect that they have on driving behaviour (although these have been studied and considered). This constraint is necessary to cut down the complexity of the computational model and simulation implementation at later stages. The strategy is to develop a driver behaviour model that is a good foundation for future research. The model can be expanded with more complex human interactions and emotions. At this point in time these complex motives and intentions based on emotions are beyond what is feasible using the current computer simulations available.

1.5. Approach

First a literature study of the relevant domain specific information was conducted, including the areas of traffic safety, human factors engineering and traffic psychology. Human factors engineering provides a foundation to model human capabilities and decision making (cognition), using traffic engineering as a back drop to provide a context to work in. Traffic psychology has a number of models that can be used in conjunction with human factors engineering, which was used to develop a conceptual framework that is suitable for further development as a computational model.

In this phase of the graduation project the focus will shifted to the actual development of a software design based on algorithms from the field of artificial intelligence and other areas that will eventually produce a computational model which can be implemented in the simulation environment.

In broad terms this research, along with the literature study, forms the basis for the final graduation project during which the actual driver behaviour model will be implemented. Globally, the following approach can be sketched:

i. **Literature study:**
   a. Traffic engineering
   b. Human factors engineering
   c. Psychological models
   d. Simulation environment

   ⇨ **Result**:
   - Development of a conceptual model.
   - Domain specific knowledge base for further, more concrete research.

ii. **Graduation project:**
   a. Development of a computational model
   b. Design
   c. Implementation
   d. Debugging and testing
   e. Simulation and results analysis

   ⇨ **Result**:
   - Simulation incorporating a driver behaviour model.

1.6. A personal note

Since I am neither a traffic engineer, nor a psychologist or well versed in the area of human factors engineering I had several reservations embarking on this project. However I enjoyed studying these interesting areas of research, especially psychology which has long interested me but I have unfortunately never had the time to pursue this interest. Since I am software engineer I will apologize in advance for any naivety displayed on my part in these areas and remind the reader, that being a software engineer, I am focused on creating models that can be implemented in algorithms.

Chapter

2

2. Traffic Engineering

In this chapter concepts from traffic engineering that are relevant to simulation will be introduced.

Since accidents occur so infrequently traffic researchers and engineers sought another metric to measure traffic safety. Additionally in many simulations collisions do not "physically" occur as the simulated vehicles simply drive through each other and continue on their way - as is the case with MARS, a collision detection system has not been implemented. These considerations lead to the development of conflict theory and surrogate safety measures, these two concepts will be explained. The theories presented are specific to traffic simulations (MARS has an extensive logging system that records pertinent information pertaining to safety measures).

2.1. Conflict theory

In essence conflict theory is formulated on the basis that conflicts, in which two or more drivers are converging on a collision course and will collide if one or all of the drivers do not take some sort of action to avoid the collision. These types of conflicts happen far more often than actual accidents. Making these conflicts easier to research and useful as a relative measure of safety for a given traffic system. Before continuing we will first present the formal definition of a conflict, taken from (Gettman & Head, 2003) :

Conflict

An observable situation in which two or more road users approach each other in time and space to such an extent that there is a risk of collision if their movements remain unchanged.

If we consider common situations while driving then there are several likely conflicts that could emerge. Figure 1 shows some of the most common conflicts.

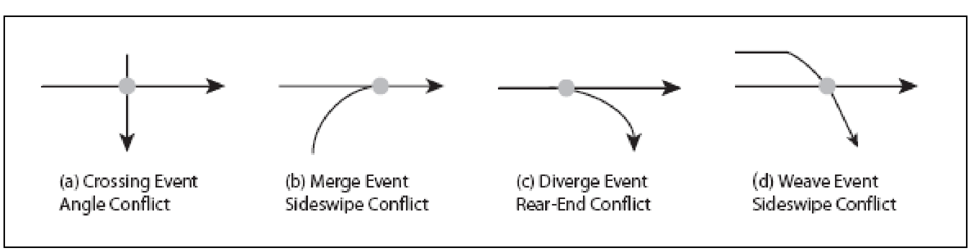

Figure 1 Different types of conflicts (Abdoelbasier, 2005).

Based on these different conflicts that occur we can define two more specific types of conflicts (Gettman & Head, 2003):

Conflict point

The conflict point represents a fixed location in space where the crossing flow intersects with the flow proceeding straight through the intersection (Figure 1.a).

Conflict line

The conflict line represents a region of space where the preceding vehicle conflicts with a following vehicle in the same lane. This can be true of:

- Vehicles entering the lane from across street in front of a vehicle proceeding straight (Figure 1.b).
- Vehicles travelling in the same direction when the leader decides to turn left or right abruptly (Figure 1.c).
- Vehicles changing lanes in front of another vehicle, causing braking by the follower to maintain a safe following distance (Figure 1.d).

These conflicts enable us to study traffic situations, but we need some measure that can be applied to these conflicts such that the simulation can yield a quantitative measure of safety, this leads us to the notion of surrogate safety measures.

Statistically more accidents occur on rural roads and intersections than on highways

2.2. Surrogate safety measures

Surrogate safety measures or safety indicators are used to derive data from traffic simulations for the purpose of evaluating safety. These safety measures either relate to the likelihood of an accident occurring or how severe the accident would be (safety measures related to the geometry or location are also sometimes defined). Several surrogate safety measures have been defined. Some of the most interesting and common safety measures are described in Figure 2. Using these safety measures various calculations can be carried out to evaluate the safety of a situation, the exact details of which will not be discussed here as these have already been described in depth by (Abdoelbasier, 2005). These measurements and calculations have already been built into the MARS logging system and therefore will not be discussed further.

SSM	Type	Description
TTC	l	Time to Collision – Expected time for two vehicles to collide if they remain at their present speed and on the same path.
ET	l	Encroachment Time – Time duration during which the turning vehicle infringes upon the right-of-way of through vehicle.
PSD	l	Proportion of Stopping Distance – Ratio of distance available to manoeuvre to the distance remaining to the projected location of collision.
DR	l	Deceleration Rate – Rate at which crossing vehicle must decelerate to avoid collision.
PET	l	Post-Encroachment Time – Time lapse between end of encroachment of turning vehicle and the time that the through vehicle actually arrives at the potential point of collision.
IAPT	l	Initially Attempted Post-Encroachment Time – Time lapse between commencement of encroachment by turning vehicle plus the expected time for the through vehicle to reach the point of collision and the completion time of encroachment by turning vehicle.
TET	l	Time Exposed Time-to-collision – The duration of exposition to safety critical TTC values over specified time duration H. [*Minderhoud and Bovy*, 2001]
TIT	l	Time Integrated Time-to-collision – The TIT indicator uses the integral of the TTC profile of drivers to express the level of safety (in s^2). [*Minderhoud and Bovy*, 2001]
v_{max}	s	Maximum of the speeds of the two vehicles involved in the conflict event.
Δv	s	Maximum relative speed of the two vehicles involved in the conflict event.
CPL	g	Conflict Point Location
CLSP	g	Conflict Line Starting Point
CLEP	g	Conflict Line Ending Point

Figure 2 Generally accepted surrogate safety measures, l = likelihood; s = severity; g = geometry or location (Abdoelbasier, 2005).

Chapter

3

3. Human Factors Engineering

In this chapter human decision making and the factors influencing this process will be studied, providing insight into human capabilities, limitations and errors associated with this process.

Human factors engineering deals with how humans interact with each other and the system they function in. Of particular interest is the interaction between drivers and the traffic system they operate in. Human factors play an important role in traffic safety, as much as 90% of all accidents are due to human errors (Wickens, Lee, Liu, & Gorden Becker, 2004). Human factors engineering attempts to explain the decisions humans make using notions from fields such as psychology and neural science. This research focuses on the aspects of human factors that affect driving and traffic safety, specifically those factors that may contribute to accidents.

Human factors need to be introduced because these factors will be combined and attributed to different behaviours that will ultimately affect driving in the simulation environment. Human factors are also a source of reliable and concrete concepts, which can be quantified and easily added to a computer simulation.

3.1. Cognition

Cognition deals with the way people perceive the environment around them, how humans think and remember. According to (Durso, 1999) there are three stages in cognition:

1. Perception of information about the environment
2. Processing or transformation of that information
3. Responding to the information.

Many stages of information processing depend on mental or cognitive resources, a sort of pool of attention or mental effort that is of limited availability and can be allocated to processes as required (Wickens, Lee, Liu, & Gorden Becker, 2004). The human eye for instance can only focus on one thing at a time, and most people can only handle a few tasks at a time. How well and to what extent these capacities can be utilized is affected by emotional and physical state, age, the environment and various other factors. The exact effect that each of these factors has on cognition will be discussed in greater detail in the following sections. Needless to say degraded cognitive ability has significant effects on the driver and traffic safety.

3.2. Perception

Information about the world around us is received by various sensory organs these can be referred to as channels. Perception deals with extraction and analyses of raw sensory data (from various channels) in such a way that meaningful information is produced that can be used for further mental processing. There are many factors that can degrade the level of perception (i.e. how well something is perceived) such as weather conditions (poor visibility), intoxication, age and the affective state of the driver.

3.3. Attention

Attention is an important contributing factor in traffic safety. A major cause of automotive accidents is a lack of attention (or being distracted while driving) (Malaterre, 1990). Selective Attention, or what we pay attention to, is influenced by four factors: salience, effort, expectancy and value (Wickens & Xu, 2003).

Salience is attention capture, which is stimulus driven, such as a driver honking the horn, focusing our attention. Expectancy and value deals with what we look at or how people sample the world around us and where people expect to find that information. The frequency of looking at or attending to a channel is also modified by how valuable that source is deemed or by how costly it would be to miss an event from that channel (Moray, 1986).

Expectations are based on past experiences, high expectations similarly are based on events that occurred or were encountered frequently in the past. The use of past experiences is related to the memory of a person and is discussed in more depth in the next section.

Finally, the effort we put into monitoring a channel is normally inhibited by amount of effort it takes, this is often the reason that drivers do not check their blind spots when changing lanes as it requires more effort than simply looking in the mirror.

3.4. Memory

There are two main forms of memory, long term and short-term memory. Short term memory or the working memory is transient, acting as a short-term store for use by other cognitive transformations. Long term memory is made up of what we have been taught or learned and contains our general knowledge on facts and procedures.

Experiences expose the perceiver to sets of experiences and current events or situations. These experiences that are recognized as being similar to the current situation are stored in long term memory, these sets are said to become “unitized”. Unitization allows for more rapid/automatic responses to information. A unitized set allows part of the perception processing to be skipped, increasing the reaction speed to a situation (Wickens, Lee, Liu, & Gorden Becker, 2004). This also explains why experience (through practice or training) plays such an important role in traffic safety, and for this reason is often associated with age – the adage: the older, the wiser.

There are various limits and factors that influence how short term working memory functions. Working memory is limited to approximately 7 chunks of information at any one time, meaning that the average person can only keep track of about 7 different things simultaneously. Additionally this information can only be held for a short amount of time and tends to decay rapidly. These limitations on working memory mean that short term memory is affected by attention, availability of resources and other factors, such as alcohol, fatigue and the affective state.

3.5. Situational awareness

Situational awareness is the awareness that a person has about the changes in the dynamic system that makes up a person's environment. Many accidents result from the lack of situational awareness. Situational awareness also allows one to make projections and predictions on how the environment will change. How well a person's situation awareness performs is based on how successfully the resources (cognitive abilities) are allocated, the demand on resources and similarity of tasks that must be carried to meet the task at hand.

3.6. Decision making

The decision making task is generally defined as a mental process that a person must carry out to achieve a particular goal or task. There are usually several different alternatives to choose from. There is usually information available with respect to the options, some amount of time (longer than a second) to make the decision and a related amount of uncertainty. In human factors engineering the decision making process can be divided into three stages. First information is acquired and perceived (relevant to the decision). Next, hypothesis and situational assessments are made pertaining to the current and future state relevant to the decision. Lastly, planning and the selection of what action to take based on the inferred state, costs and values of different outcomes (Wickens, Lee, Liu, & Gorden Becker, 2004).

There are two different flavours of decision making models. The first is based on what people *should do* based on rational reasoning or by calculating the probabilities of success and the evaluation of potential costs and benefits associated with a specific decision. However humans do not necessarily choose the most rational, or most optimal, decision. This normative model is often associated with game theoretic models and concepts.

The fact that human decision making frequently does not conform to the rational thinking prescribed by the normative model, led researchers to develop another decision making model – the descriptive model. These researchers believed that rational consideration of all factors associated with all possible outcomes is just too time-consuming and effort demanding (Wickens, Lee, Liu, & Gorden Becker, 2004).

The descriptive model suggests that people instead use a simpler and less complete decision making process, working by way of simplification and rules of thumb – heuristics. These shortcuts can however lead to bias decisions resulting in poor decisions, which can eventually end in systematic errors.

3.7. Arousal

The level of arousal (psychological stimulation) also has an effect on the performance. For instance, a person driving on a boring road for a long time may be bored and become complacent reducing performance and safety due to poor vigilance. Conversely, if a person is on an extremely congested road, with rowdy children in the back, this high workload could cause driving performance to suffer. The theoretical optimum level of arousal is shown in Figure 3. Before and after this optimum the level of performance can suffer significantly.

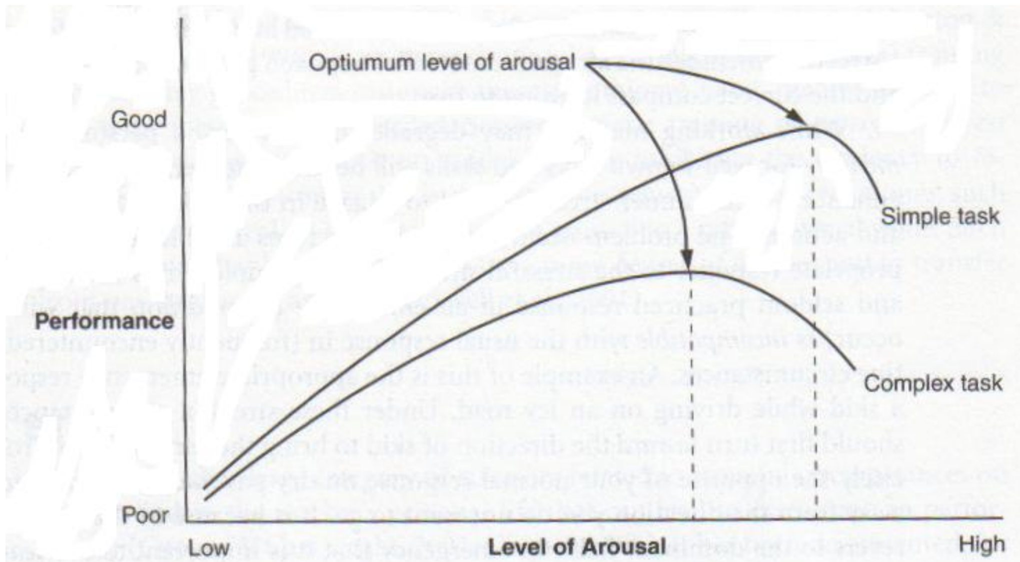

Figure 3 Yerkes-Dodson law showing level of arousal (induced by stress) and performance (Wickens, Lee, Liu, & Gorden Becker, 2004).

3.8. Workload and fatigue

The concept of workload can best be described by the TR/TA ratio, which is the time required to carry out a task compared to the time available. A person is said to be overloaded when this ratio drops below one. Obliviously, when a person is overloaded, performance will suffer - this relationship is illustrated in Figure 4.

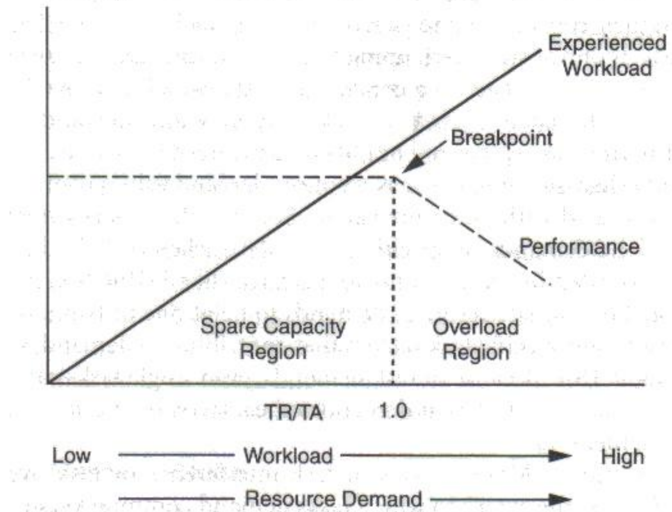

Figure 4 The hypothetical relationship between workload imposed by task (Wickens, Lee, Liu, & Gorden Becker, 2004).

Besides degraded performance, high workloads can also have an accumulated effect eventually causing fatigue. Fatigue can cause continued loss of performance even if the workload is lowered to a more manageable amount. Fatigue can negatively affect the concentration and therefore a driver's attention and alertness.

3.9. Age

Empirically seen there is a strong relationship between age and traffic accidents, this can be clearly seen in

Figure 5 shows the number of fatalities as a percentage of the total drivers for a given age group that are in possession of a drivers licence. At a young and old age relatively more fatalities are recorded.

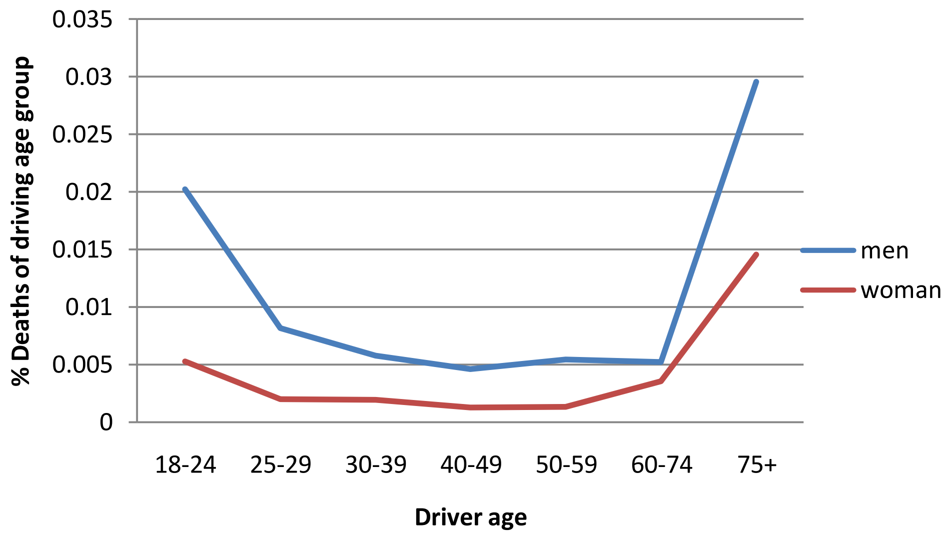

Figure 5 Driver deaths percentage of driver population split per age group from 2007 in the Netherlands (CBS, 2008).

Several reasons for this phenomenon can be pointed out. The relatively high number of fatalities registered at a young age (18 – 24 years) can best be attributed to the lack of skills and experience of young, new drivers. Additionally young drivers take more risks due to overconfidence (Brown, Groeger, & Biehl, 1988) and are more likely to drive under the influence of alcohol. After several years of driving experience starts to pay off and the number of fatalities drop rapidly. From around 60 years and onwards there is a marked increase in the number of fatalities. The most plausible explanation is the fact that the cognitive abilities and reaction speed in elder people starts to degrade, effecting driving ability.

3.10. Alcohol and drugs

Driving under the influence of alochol or drugs has a significant effect on reation time and the cognitive abilities of the driver. A blood alcohol concentration of 0.08% already increases the chance of an accident by more than double (HSRC). With a blood alcohol level of 0.18% the chances of an accident increase by a factor of 30. A recent study from the university of Leiden and Amsterdam found that even causal users of cocaine will suffer as much as 25 miliseconds delayed reaction speed. This is short but could be critical in traffic situations and mean the difference between crashing or not (van Oord, 2008).

Younger drivers are more likely to drive under the influence of alcohol and is therefore one of the reasons that this age group comprises a large percentage of total fatalities (DHHS, 2004). Drug use has a similar trend. Interesting is how the use of alcohol is distributed over gender. Men are the biggest violators by far, 85% of all violations are committed by men (Rijkswaterstaat, 2006).

3.11. Summary

There is an underling structure between the different factors. There is an overlap in the form of "cause and effect" relationships between the different factors - mapping these relations is key to creating the driver behaviour model. These human factors will be combined and attributed to specific behaviours.

Chapter
4

4. Driver Psychological Model

In this chapter the psychological model, developed by Ray Fuller, which was selected as a conceptual basis in the development of a driver behaviour model will be presented. Important considerations related to creating a driver model, first introduced by Michon, which served as a fundamental and guiding concept during this project will also be discussed. Theories related to Fuller's model will also be included.

In the literature research phase of this project various psychological theories and models (specific to driving) were studied and a model created by Ray Fuller was selected to form the conceptual basis for the development of a driver behaviour model. Fuller's model was found to be the best suited psychological model. The model is practical and can be used to develop a conceptual framework that can be efficiently translated into a computational model (Absil, 2008).

Fuller's model is, to a certain extent, a hybrid or combination of other models and theories, and where necessary some of these concepts will also be described. One of the concepts that repeatedly appear in psychological models is the concept of risk, which will also be discussed. Finally some remarks, largely based on Michon's research will be discussed. Michon's remarks on the general approach to creating a model of a driver has been one of the most important, fundamental and guiding concepts during this project. Michon (Michon, 1989) introduced a simple model describing the driver's task, this model will be presented first.

4.1. The driving task division

One of the most prominent models, first described in (Michon, 1989), divides the driver's task into three levels, as shown in Figure 6.

Driving task

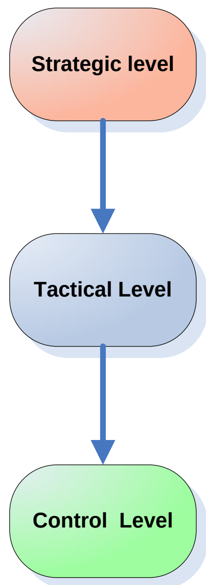

Figure 6 Michon's driving task hierarchy.

In his research Michon suggests that the driver task can be split into three stages or levels of operation. The first level, the strategic level, deals with high level decision making. Examples are route selection or changing the route during the trip in response to congestion and when to leave.

The next level deals with tactical decisions focusing on choice of manoeuvres such as lane changing, speed selection and overtaking.

The lowest level deals with the actual control of the car, such as maintaining speed, the actual angle to steer the car at through a turn and how hard to push the brake pedal to slow down on time.

While driving there are two competing objectives that can be recognized; efficiency - the driver wants to reach his destination as soon as possible, but also safely. These two objectives can be in stern contrast to each other. A driver that is late may speed in order to arrive at meeting on time, thereby compromising his chances of arriving safely (due to the increased risk associated with speeding).

Tasks on the control level are important during driving. Staying in a lane and successfully executing a turn without crashing are critical to safety. A failure in a control task will often lead to an accident. Related to the control level of the driving task, expected events are dealt with faster than unexpected events. For instance, people do not expect the driver ahead of us on an uncongested highway to abruptly come to a full stop. Most people would not have experienced such an event before. Reaction speed and motor coordination obviously play an important role at this level.

4.2. Fuller's model: The Task-Capability Interface Model

Fuller proposed several models, starting with a model based on avoidance of potential aversive consequences (Fuller, 1984), followed by the task-capability interface (TCI) (Fuller, 2000). Refinements of this model followed in (Fuller & Santos, 2002) and (Fuller, 2005).

In (Fuller & Santos, 2002), a framework that can be used to understand a driver's behaviour was developed. This framework is constructed by looking at various parts of driving from a "snapshot" or "freeze frame" perspective and is instructive in understanding the various elements of driver behaviour that contribute to the driver's way of driving. The model developed by Fuller that emerges out of this framework is simple and intuitive.

While presenting this model there will be references to human factors engineering which come back in Fuller's model. The link between human factors engineering and psychology combined in one model is what makes Fuller's model interesting.

The task-capability interface model relies on the notion of task difficulty homeostasis which is to certain extent an attempt by Fuller to reconcile and combine risk homeostasis theory and the Taylor study. To motivate this notion of task difficulty homeostasis we will start by describing the rest of the TCI first.

4.2.1. The driving task

Driving requires the driver to carry out several tasks based on external and intern stimuli, such as responding to other traffic or executing a turn so as to stay on route, to safely reach a destination. On occasion drivers will have to respond to unexpected situations, but mostly the drivers will perform planned actions which are shaped by their expectations and the unfolding traffic situation (Fuller & Santos, 2002). Several factors influence the driving task, these are schematically displayed in the Figure 7 below.

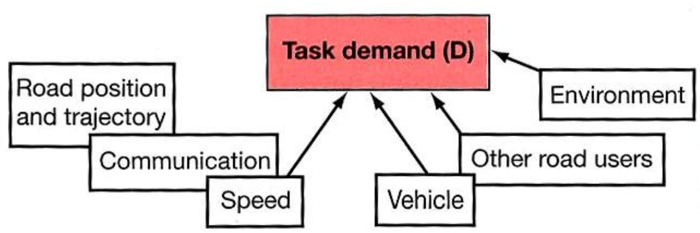

Figure 7 Contributing factors to demands on the driver (Fuller, 2000).

In (Fuller & Santos, 2002), the tasks that the driver must carry out in order to drive safely are considered first. The driver must process various sensory inputs, such as visual data. Then process that information and carry out appropriate actions. In general, barring an unexpected event, such as another car "cutting" in front of the driver, for example, the driver carries out planned actions based on expectations in the current traffic situation. The following Figure 7 depicts the model describing the driving task.

The demand of the driving task, *D*, is influenced by the environment and other physical factors with which the driver may interact. For instance, speeding and heavy congestion may cause the demand of the driving task to increase. It should be noted that speed is an important factor in Fuller's model, as it is the main way the driver can influence the difficulty of his driving task (Fuller, 2000).

4.2.2. Driver capability

Next the driver himself is considered, as different drivers have different behaviours and attributes which enable them to deal with the demands of the driving task. In (Fuller & Santos, 2002) these are known as the constitutional characteristics of the driver and describe the factors that the driver has to drive effectively and safely. Driver capability is based on the individual's competences, such as motor skills, cognitive ability, reactions and skill. Education and experience define the upper limit of a driver's capability. In addition to these factors a range of variables (human factors, see chapter 3) which include fatigue, emotions, stress, distractions, effects of drugs or alcohol and motives like aggression can also affect the driver's capability. These factors are schematically related to each other in Figure 8 below. The combination of all these factors eventually yields the driver's capability.

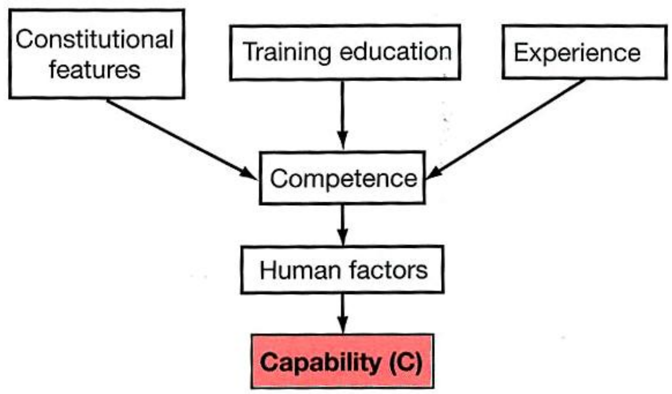

Figure 8 Determinants of driver capability (Fuller, 2000).

4.2.3. The task-capability interface

Combining the driver capability and the task demand produces an interface between the two. If the demand of the task(s) exceeds the driver's current capability then the driver may be overwhelmed and lose control. Conversely, if the driver's capability is greater than the demand of the task at hand, then the driver is in control and can safely continue. This relationship is shown in Figure 9.

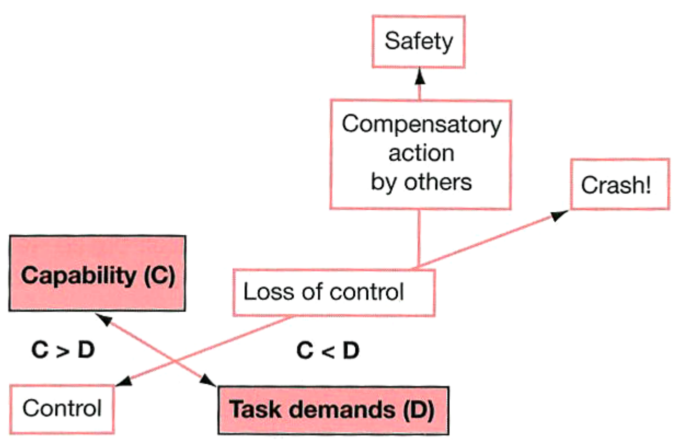

Figure 9 Outcomes of the dynamic interface between task demand and capability (Fuller, 2000).

Note that the model shows the demand and capability as separate entities, but this is not necessarily true. For instance, a high level of demand may eventually cause the capability of the driver to deteriorate due to fatigue cause by the stress and excessive workload. A low level of arousal can also have a negative affect, resulting in lower vigilance and inattention. Losing control does not necessarily mean that the driver will be involved in a crash. Another driver could make an evasive manoeuvre to avoid the collision or the driver himself may be able to (luckily) take corrective action. The extension of the model to accommodate this phenomenon, creating the task-capability interface, is show below in Figure 10.

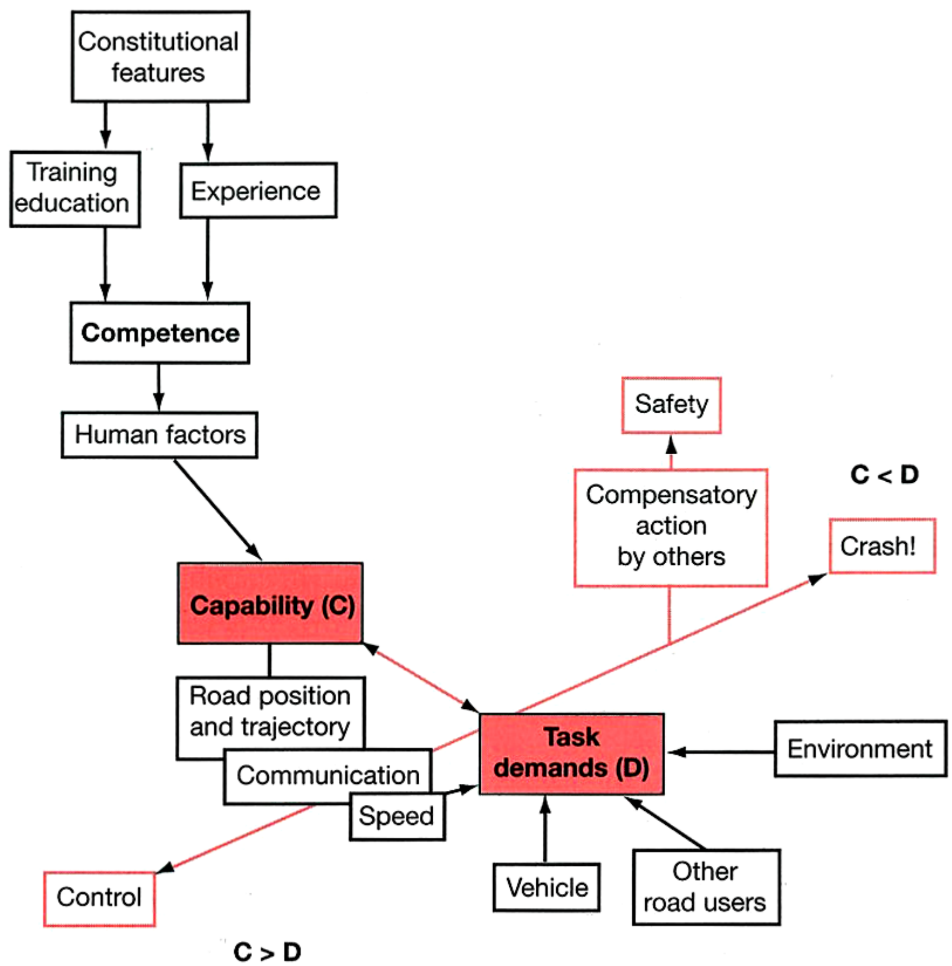

Figure 10 The task–capability interface model (Fuller, 2000).

The basis of the Fuller's model is now complete, it however it lacks a mechanism to "drive" it. Next a dynamic mechanism will be described. First however the concept of risk homeostasis must be introduced.

4.3. Risk Homeostasis

Homeostasis refers to a dynamic process which attempts to maintain a stable target level through adjustments and regulation mechanisms. The process by which living organisms regulate their internal state so as to maintain a stable condition is an example of homeostasis.

Any system that has homeostatic properties exhibits fluctuations. These fluctuations are caused by delays in detecting and making adjustments to reach the desired target level. This means that the actual level fluctuates around the target level, consequently a homeostatic process makes it possible to extract long term steadiness form short-term fluctuations (Wilde, 1994).

Homeostasis detects and makes adjustments to regulate a system in order to achieve a desired level through a negative feedback mechanism. Homeostasis is a self correcting mechanism. Wilde uses the concept of homeostasis to explain how people deal with risk. In his book (Wilde, 1994), Wilde summarizes the theory of risk homeostasis as follows:

> *Risk Homeostasis Theory maintains that, in any activity, people accept a certain level of subjectively estimated risk to their health, safety, and other things they value, in exchange for the benefits they hope to receive from that activity (transportation, work, eating, drinking, drug use, recreation, romance, sports or whatever).*
>
> *In any ongoing activity, people continuously check the amount of risk they feel they are exposed to. They compare this with the amount of risk they are willing to accept, and try to reduce any difference between the two to zero. Thus, if the level of subjectively experienced risk is lower than is acceptable, people tend to engage in actions that increase their exposure to risk. If, however, the level of subjectively experienced risk is higher than is acceptable, they make an attempt to exercise greater caution.*

Figure 11 provides a simplified version of Wilde's risk homeostasis mechanism that Fuller used in an earlier version of his model (Fuller & Santos, 2002). In this model the driver has a "target risk" (the risk that the driver is willing to accept), which the driver continually compares the "his perceived risk". The driver makes changes to his driving to bring the perceived risk and target risk to the same level. So if the perceived risk is higher than the driver's desired target risk the driver will behave more cautious – lowering the perceived level of risk.

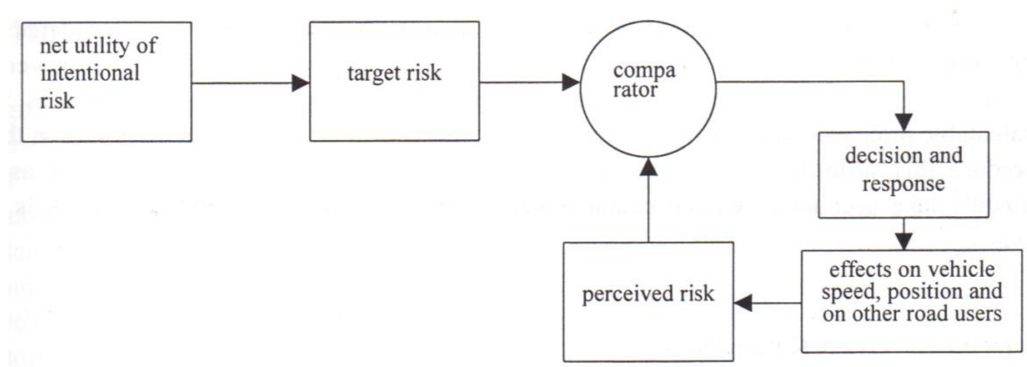

Figure 11 Simplified representation of risk homeostasis (Fuller & Santos, 2002).

Why people take or accept a level of risk higher than zero according to Wilde is shown in Figure 12. Moving along the horizontal axis the exposure to risk of an accident increases (due to increased speed or amount of driving) and the associated expected gain (y_1) and loss (y_2) increases. The net benefit rises, reaches an optimum and then starts to decline. At zero subjective risk the net benefit is zero. With extreme high risks the expected loss outstrips the potential gains causing the net benefit to become negative. For this reason most people will select some risk to avoid the two extremes mentioned. Wilde argues that people set out to maximize their net benefits resulting in a risk level above zero – this is the core of risk homeostasis theory.

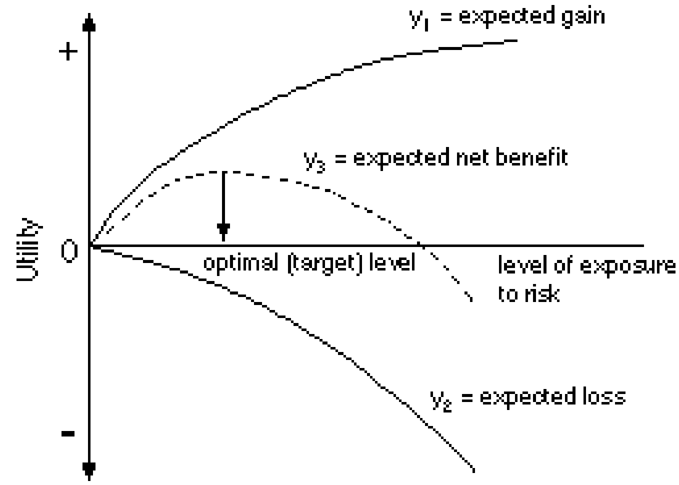

Figure 12 Theoretical representation of road users as net benefit maximizes as risk optimizes (Wilde, 1994).

Risk compensation is the theory that individuals will change their behaviour in response to perceived changes in risk (it is self-evident that individuals will behave more cautious if their perception of risk or danger increases). Risk Homeostasis is an extension of this theory

Risk compensation is widely accepted, risk homeostasis is not. Proof of risk compensation is provided in several studies, the most famous of these is the Munich taxicab study (Aschenbrenner & Biehl, 1994), in which one half of the cabs were fitted with new anti braking system (ABS) brakes, the other half with conventional brakes. The accident rate for the cars with the new ABS brakes was expected to be lower. However the accident rate for both groups of taxicabs remained unchanged. Wilde explains this phenomenon with risk homeostasis theory, suggesting that the addition of the ABS brakes meant that the taxi drivers felt safe and hence took more risks, maintaining their original target risk level.

As evidence for risk homeostasis theory Wilde uses the decision to switch from left-hand driving to driving on the right-hand side in Sweden and Iceland. Almost immediately after the traffic was changed to right-hand driving, the accident rate per head of population dropped dramatically. However after sometime (less than two years) the accident rate returned to the pre-existing trends. Wilde claims that this phenomenon is a result of risk homeostasis. The impact of changing over caused drivers to significantly overestimate the danger, this perceived fear was much higher than the target level of risk drivers were willing to accept, causing drivers to behave unusually cautious. This extreme cautiousness drove people to adjust their driving pattern, after sometime the perceived risk normalized and eventually approached the target level of risk. At this point people returned to their normal driving behaviour which resulted in the accident toll returning to what is was before the switch.

4.3.1. Remarks

It would seem that there is a significant amount of empirical evidence that can be used to support Wilde's theory of risk homeostasis, yet the theory has garnered much criticism. Michon, for instance, in (Michon, 1989), makes the following observations and comments on Wilde's theory. Risk Homeostasis assumes that (1) risk homeostasis is an individual propensity and (2) that the collection of homeostatic behaviours of individuals does account for the homeostatic behaviour of the collective. However, Michon argues that the assumption that the same homeostat is operating in all individuals is implausible, since assuming that human behaviour is in some way generic is flawed. Even though Wilde's theory seems to make common sense, it does not really describe collective behaviour. This is largely due to the fact that the model describes the central tendencies of an idealized driver, creating 'prototypical' descriptions, based on average behaviour of the whole population, which rest heavily on the assumption that the average driver, on the whole, will act rationally. If drivers would behave in a rational way, a great deal could be predicted given the driver's intention and environmental information, unfortunately this is not the case.

Vaa has several criticisms of risk homeostasis theory, but does acknowledge the following characteristics of the theory:

- Risk homeostasis is frequently discussed and central to many theories.
- Risk compensation is addressed [In Risk Homeostasis], which definitely exists
- It may represent a "dead-end" theoretically, as it is not suitable for testing, but "There is something in it, after all!" (Vaa, 2001).

Risk compensation can only be considered from the point of view of studies of driver behaviour in the sense of aggregate behaviour, such as probability distributions. Risk compensation cannot be applied to individual drivers, but merely as a tendency for motivational satisfaction (Summala, 1988).

Vaa however believes that the "right track", in contrast to Wilde's theory, is represented by the Zero risk model by Näätänen & Summala, which is based on the Taylor study. This theory suggests that drivers try to avoid risk by regulating their behaviour according to a perception of risk, while Wilde's theory states that drivers seek a particular risk level, greater than zero.

Vaa also warns that risk homeostasis model (Vaa, 2001):

> *"somehow assumes a powerful, hidden, unconscious force that forces you (and everyone else too!) to act in such a way that the target level of risk is sustained individually for everyone as well as for everybody else at an aggregate level".*

This seems analogous to Adam Smith's "invisible hand" described in his work The Wealth of Nations, which has also been widely discussed and criticized: *"the reason that the invisible hand often seems invisible is that it is often not there."* – Joseph E. Stiglitz.

Vaa continues by pointing out that:

> *"Wilde is inaccurate in his choices and definitions of concepts. "Cost" and "benefits" is central to the model but they are not defined in psychological terms. As they are presented, they adhere more to the limitations of economic utility theory, not to a wider understanding of behaviour in psychological terms".*

A problem inherent to Wilde's model is that it is difficult, perhaps even impossible to assign values. Wilde himself states in (Wilde, 1994) that the values should not be used explicitly in calculations.

4.3.2. Homeostasis in Fuller's model

Fuller uses task difficulty homeostasis, instead of risk homeostasis, and attempts to integrate work done by Näätänen and Summala (Näätänen & Summala, 1974), based on the Taylor study, but still account for risk in the following way:

> *As long advocated by, for example, Näätänen and Summala [1976], driver motivation is for a crash risk of zero. Where risk varies for the driver is in terms of the experience of variations in the difficulty of dealing with driving task demands to achieve a safe outcome. It is thus postulated that as task difficulty increases (above a minimum level), so does the experience of risk. (Fuller, 2000).*

Just as in risk homeostasis theory, Fuller suggests that a driver tries to maintain a target level of difficulty (Figure 13), this is mechanism functions similarly to the model shown in Figure 11). If the situation becomes too demanding the driver can slow down, thereby also lowering his task difficulty. Likewise, if the task is too easy, even boring, the driver may speed up to make things more challenging. Even though this seems very much like risk homeostasis, Fuller warns that they are not necessarily the same.

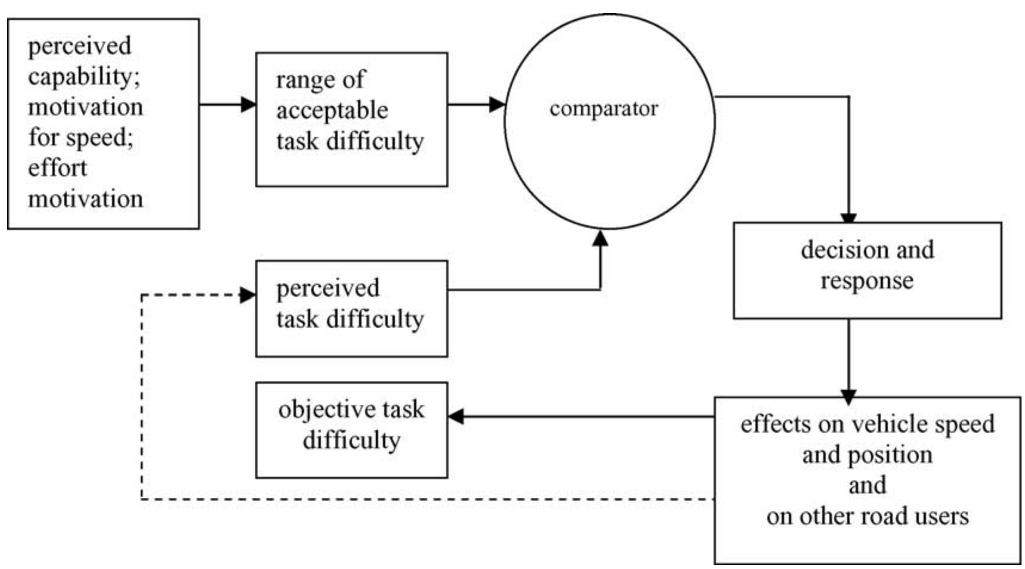

Figure 13 Task difficulty homeostasis (Fuller, 2005).

Fuller also suggests that this model may influence the strategic level of a drivers decision making process, as a driver may choose another route based on the difficulty associated with it (Fuller, 2005). To keep the level of complexity of the simulation low no attention will be paid to the interaction between this conceptual model and the strategic level of a driver's decision making.

Figure 14 below shows that the perceived difficulty and risk are highly correlated.

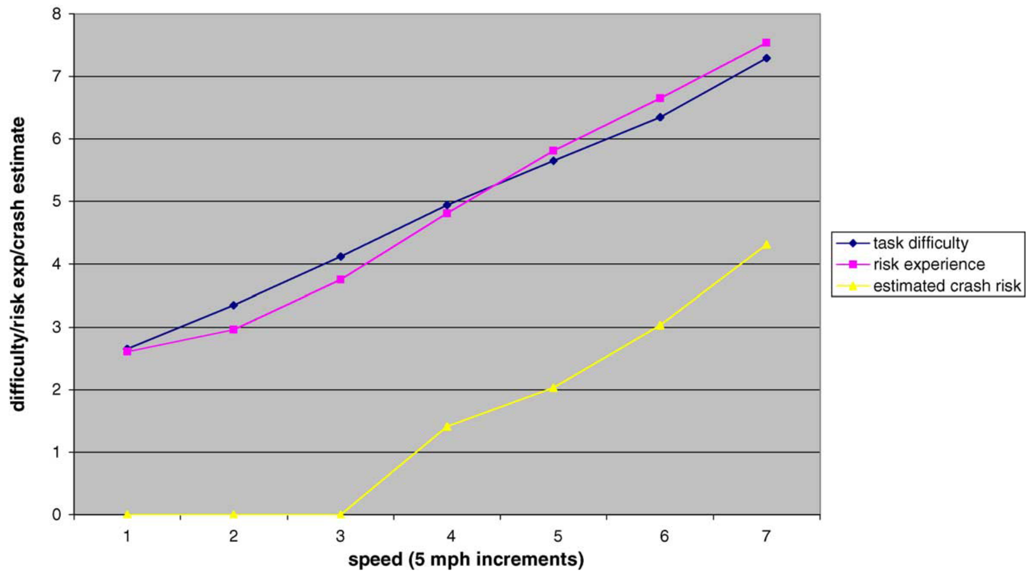

Figure 14 Ratings of task difficulty, estimates of crash frequency and ratings of risk experience for the country road scenario (Fuller, 2005).

Surprising (for Fuller as well), is how strongly the subjective difficulty correlates to the subjective risk (Figure 14). People do not actually calculate risk, but people do have a well defined sense of what is difficult and what is easy, and may use difficulty as a substitution for the calculation of risk. The difficulty of a task can theoretically also be to a certain extent quantified, which is import if this model is to be simulated, in that human factors give an indication of how hard a task will be for someone given their age for example.

Fuller used a form of risk homeostasis along with task difficult homeostasis (shown in Figure 11) in ealier models. Suggesting that under certain circumstances drivers would be willing to accept a risk of crashing greater than zero.

4.4. Michon's remarks

Fuller's model has several advantages, first of which has to do with an observation made by Michon: there are two levels of explanation regarding driver models. The rational (intentional) level generally describes the aggregate behaviour of drivers and the functional level, which deals with intra-individual information processing. Michon believes that these two levels are often confused resulting in serious theoretical problems. Fuller's model maintains this separation.

Michon goes further stating that a clear distinction must be drawn between the elementary processes and building blocks at the functional level and the complex (aggregate) behaviours generated by these elementary processes. To illustrate this relationship Michon uses the example of syntax, which can be used to generate sentences, but does not prescribe them.

There are several approaches to model human driver behaviour. Michon suggests that 'genuine' driver models are formulated at the functional level in which behaviour is modelled in terms of (mental) function and processes. Instead of assuming that the driver is behaving optimally (or rationally) the focus of attention is on actual behaviour. Since actual behaviour is usually suboptimal, the model is designed to function sub-optimally too, so as to faithfully mimic the driver's performance (Michon, 1989). According to Michon, (Michon, 1989), Fuller's model implicitly separates the functional mechanisms from the intentional, adaptive aspects of behaviour.

It is important that the Task-Capability Interface model largely adheres to Michon's guidelines. The fact that this model also uses well known principle of human factors engineering is another advantage. The model is relatively simple and intuitive.

The selection of this model is based on the consideration of how robust, practical and ease with which the model can be used as an actual framework in the simulation. The psychological model however should not be seen as an exact structure to which the software construction will strictly adhere too. The psychological model should rather be seen as a loose reference or conceptual framework for the driver behaviour model.

Fuller's model along with guiding remarks made by Michon will be combined together to form a conceptual model that is described later on in section 6.1- Conceptual Framework.

Chapter

5

5. Simulation Environment

In this chapter the Multi-Agent Real-time Simulation (MARS) will be described.

Different types of traffic simulations are available. An important distinction is the level the simulation operates on. Microscopic simulation (commonly known as a micro-simulation), allows for high resolution data collection and control. In contrast, macroscopic traffic simulations function at a higher level, focusing instead on policy influence, routing, capacity and efficiency of the traffic system. In these simulations focus is shifted away from the individual driver to the aggregate level more concerned with flows and densities. Micro-simulations focus on deriving detailed information on each individual vehicle and on providing precision control. Micro-simulation "zooms" into a small piece of the traffic network, putting part of the traffic network under a microscope as it were. MARS is a micro-simulation and is the simulation environment that will be used throughout this research.

5.1. Multi-Agent Real-time Simulation

The Multi-Agent Real-time Simulation (MARS) environment was created by TNO Science and Industry and continues to be developed. MARS allows experiments to be carried out under temporal constraints within a multi agent-framework. This allows large systems, like the traffic system, to be decomposed into independent, intelligent entities, with a resolution chosen by the modeller. The focus is on individual drivers and their vehicles which are represented as agents operating and interacting in the simulation world. MARS has been under development for close to a decade now and is primarily implemented in JAVA.

A **MARS entity** is the combination of a vehicle and driver representing an independent agent in the MARS.

The combination of a vehicle and driver in MARS is known as an *Entity*. Each entity autonomously makes decisions based on a local view of the world and traffic situation without the need for a single central controlling agent. This allows each entity have its own distinctive characteristics and capabilities.

In the formal representation of MARS, the simulation experiment is known as the model. The model describes a collection of autonomous entities (E1,2,..), which interact with each other and the surrounding world. The entities in this world are dynamic and evolve based on each entities' own internal dynamics (through internal state changes or logic). The world is a set of objects, these objects are static (i.e. their attributes cannot change). Entities can act on these objects. Objects typically represent road infrastructure or physical obstacles. Entities can have sensors (S) and actuators (A). The sensors are used to gather information about the entity's surroundings in the world. The actuators are used to create, destroy or modify the attributes of objects in the world (TNO, 2005).

Entities are represented in the world as bounded objects. Each object has attributes which are determined by the states associated with the entity. As an example, an object representing a vehicle travelling through the world, as the vehicle moves the position attribute will automatically be updated. The composition of the system into independent entities means that the behaviour (internal dynamics) of each entity is self-contained, interacting only though interfaces represented by the object's sensors and actuators. The sensors and actuators are defined abstractly, so as to keep the MARS framework generic, allowing sensors to be custom built. MARS is schematically represented in Figure 15

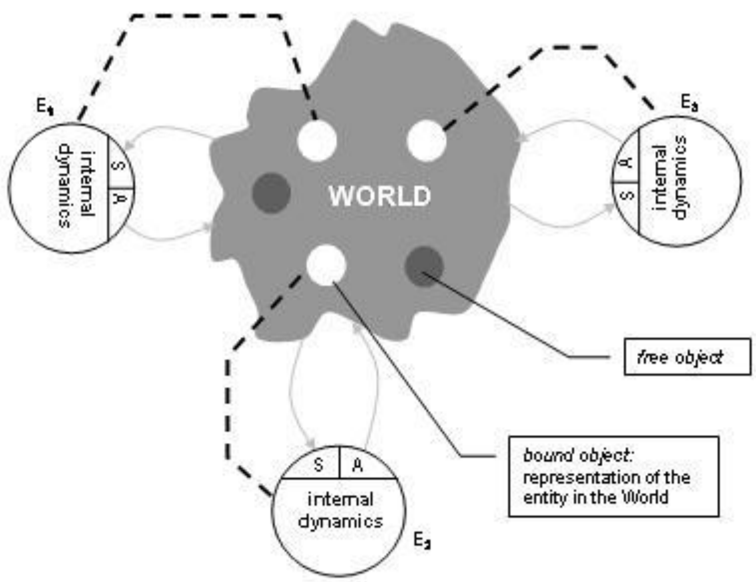

Figure 15 Entities in MARS world (TNO, 2005).

The safety measures discussed in Section 2.2 are already implemented in MARS. MARS is equipped with an extensive logging system capable of capturing all safety measures with a high degree of accuracy.

5.1.1. Structure

The MARS framework is object oriented, using objects to encapsulate an Entity. Entities have no direct communication or interaction other than through their sensors and actuators. Entities can also be composed of other entities, this encourages code reuse of low level and common components and this is the approach used to implement driver behaviour models in MARS (Abdoelbasier, 2006).

Figure 16 provides an other view of the MARS entity model. In essence MARS is a framework allowing the construction of a world model to which entities can be added.

Each entity is constructed by adding generic components, responsible for sensing and decision making, to a platform so manoeuvres and navigation are possible. The basic building block of an entity is the *Platform*, which is a simple container class, to which components can be added to model a driver and vehicle.

Although the entity model only constitutes part of the entire simulation, it is the core of MARS. References made to MARS (in the rest of this thesis) actually refer to the entity model presented here. MARS and entity model will be used interchangeably.

Conceptually MARS can be split into two parts, perception (in red - Figure 16) and decision making (in blue).

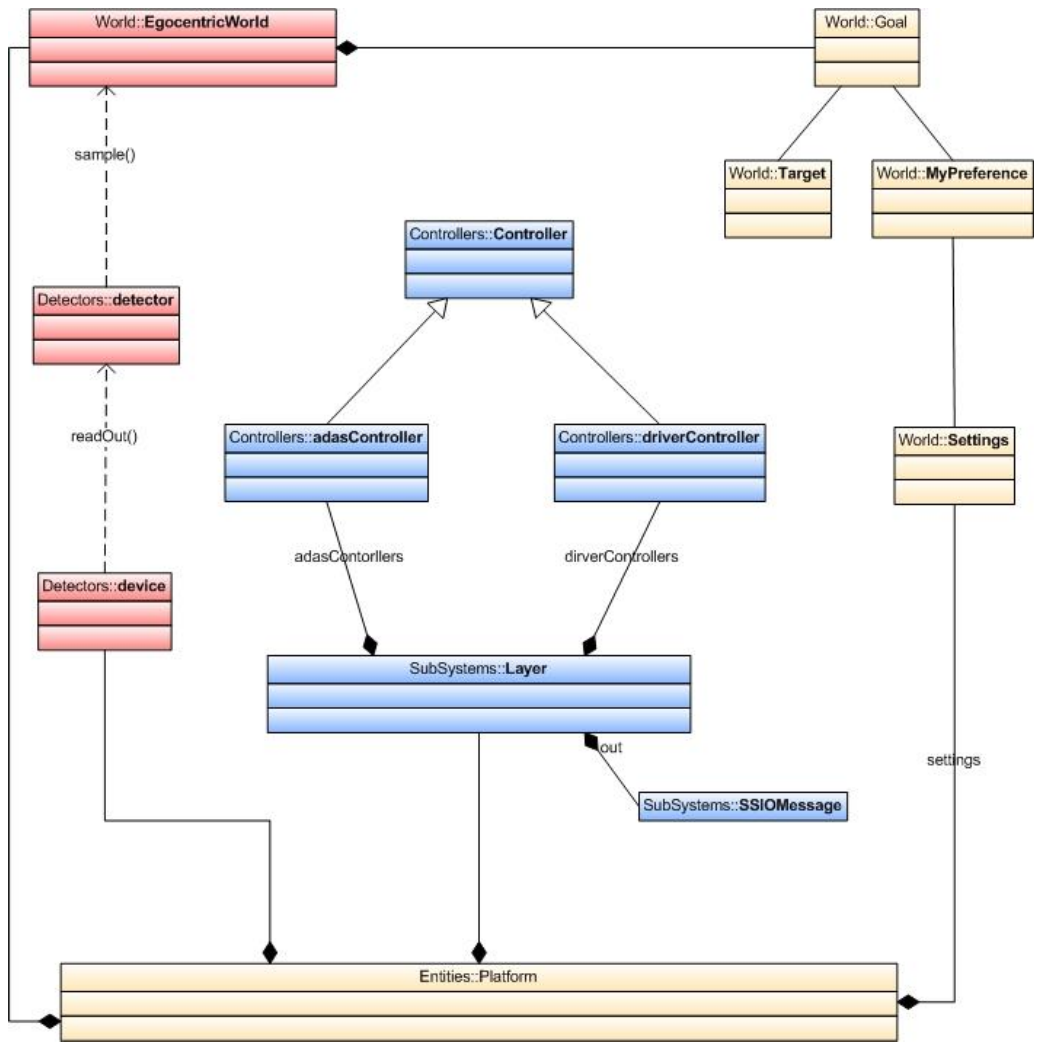

Figure 16 UML diagram of a MARS agent - entity model.

The perception part is comprised of the *Devices*, *Detectors* and the *World* (*EgoCentricWorld*). The devices are sensors that observe the surrounding world. A device can represent any kind of sensor like eyes, GPS or radar. Any form of sensor can be implemented and "plugged" into MARS. The devices produce raw sensory data. This data is collected by detectors to which the devices are connected. The information the detectors receive from the devices is perfect, by introducing a noise model the data can be "fuzzied". Adding noise can be used to simulate poor visibility for instance. Multiple devices can be plugged into a single detector. The detectors are in turn connected to the EgoCentricWorld, entities own view of the world surrounding it.

The other half of MARS (in blue, Figure 16) deals with decision making. The tasks and decisions made during driving are decomposed into individual elements and captured in *Controllers*. Controllers encapsulate the logical decision making required to manoeuvre and navigate through the world. Controllers usually handle one particular aspect of driving, so there are controllers for merging, turning, crossing, and navigating.

A single entity will generally have several controllers. These controllers are arranged in *Subsystem Layers*, shown in Figure 17. These layers are arranged hierarchically in four levels. The first three levels closely resemble Michon's driving task division (Figure 6). The navigation layer is the logically highest or most abstract layer and handles the navigation. The next layer, the coordination layer, handles actual manoeuvring in the simulation. The control level handles the actual steering and braking.

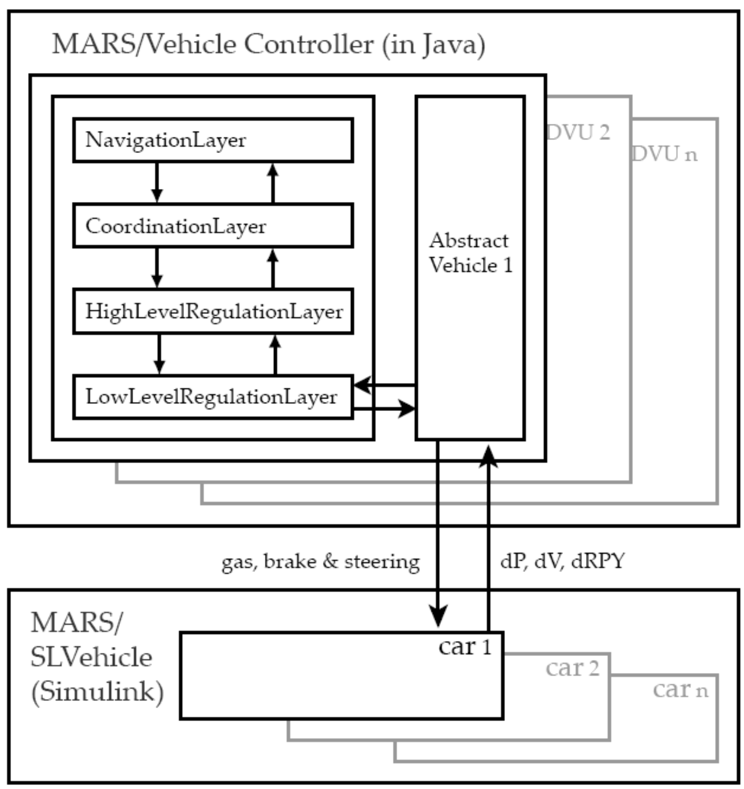

Figure 17 Hierarchical layers in MARS.

Controllers produce suggested actions, based on their own internal logic and stimuli from the outside world. Other controllers at different levels (or the same level) can act on these suggested actions. The suggested actions are simple, containing only acceleration/deceleration and a steering angle. It is possible that different controllers will produce suggested actions that are contradictory. The fourth and final level is the regulation level and is responsible for resolving any contradicting actions. The regulation layer outputs actions that control the entity's dynamics such as steering and accelerating. The resolution mechanism is simplistic using the following heuristic: if the vehicle is already braking then continue to brake. The same goes for acceleration and steering.

The *Settings, MyPreference, Target and Goal* classes contain information specific to each individual driver and vehicle. The Settings class contains parameters such as age, preferred driving speed, comfortable car following distance and many more. Each entity has a Goal (for instance drive from A to B). A target is a short term goal, for instance, to over-take another vehicle. MyPreferences contains extra settings that can be changed dynamically.

5.1.2. Limitations

MARS does not include pedestrians or cyclists in its current implementation. The current version of MARS only supports unsignalised intersections and relatively simple road constructions. While implementing pedestrians and cyclists would entail a significant amount of work, conceivably traffic lights should be implemented relatively easy. Based on these current limitations the driver behaviour model will be constrained to operation on unsignalised intersections, without pedestrians or cyclists.

5.2. Other simulation environments

Other simulation environments where initially considered in (Abdoelbasier, 2005) as alternatives, but MARS was selected as the main development platform because of its robust, flexible and extensible qualities. Other simulations could not provide the level of control and allow for modifications suitable to ongoing TNO research. This project continues the development of MARS as a micro-simulation capable of providing safety analysis specifically for unsignalised intersections.

Considerable time and effort have been put into the development of MARS, and TNO has a vested interest in continuing to develop and use MARS. For this reason other simulation environments were only briefly reviewed and considered. One of the most interesting is VISSIM, which was also considered by Abdoelbasier. VISSIM allows the tolerance for practically all variables that play a part in the simulation (such as the size of gaps that will be accepted, car following distance and speed) to be modified. Several simulation environments were considered by Abdoelbasier and eventually rejected in favour of MARS. For an overview of the different traffic simulations the reader is directed to (Abdoelbasier, 2005). VISSIM and other simulation environments were considered more as a possible reference model that could be used as a comparison for the driver model implemented in MARS.

Chapter

6

6. Driver Behaviour Model

In this chapter a conceptual model based on Fuller's model and human factors is presented. This model forms the foundation of the driver behaviour model. Concluding with a description of how the conceptual model was integrated into MARS.

6.1. Conceptual Framework

By combining the human factors and Fuller's model it is now possible to construct a conceptual framework. MARS has perception mechanisms and components that act on this perceived information, make decisions based on this information on how negotiate through the simulated world. MARS is essentially a cognitive architecture that can be influenced by different driver behaviours. An approach similar to the conceptual framework suggested here has been put forward by Raghild Davidse at SWOV (the Dutch national road safety research institute). In (Davidse, 2004), an approach was suggested to combine human factors, Fuller's model, a cognitive architecture and game theoretic concepts into a theoretical framework to study the effects of age (it is however unclear if this research was ever carried out).

6.1.1. Placing the conceptual model in context

The first step towards creating a realistic traffic simulation, with "human like" driver behaviour is the following realization, which is to place the driver behaviour model at a level above the tactical driving task (Figure 18). There are multiple reasons for this approach. The main reason for introducing the driver behaviour model above the tactical level, and not directly integrating it into the tactical level, is so that the influence of a person's behaviour filters down through the tactical level to the control level.

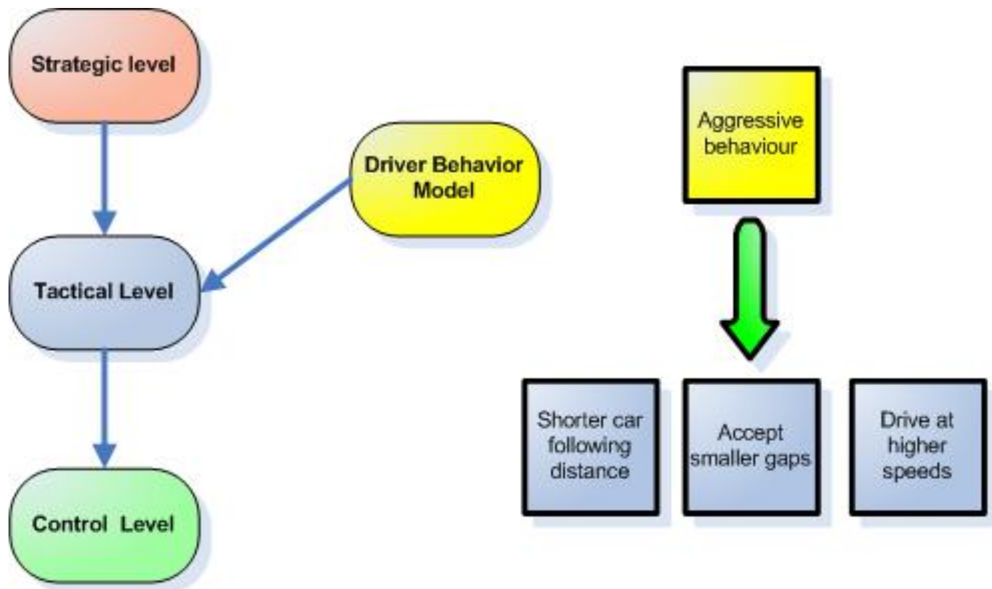

Figure 18 Placing the driver behaviour model in context (right) and the effect down of behaviour on the driving task (left).

This small and seemingly simple step is integral to this approach and has important ramifications for the conceptual model. Most research at TNO and elsewhere has focused on creating models for one aspect of safety. For instance, studying gap acceptance on its own based on the behaviour of the driver; this research is of course important, however being fatigued or driving aggressively not only affects the sizes of gaps that the aggressive driver will accept, but also the driving speed, overtaking and tailgating behaviour.

This relationship between driver behaviour and the way that people drive leads to another important feature of Figure 18 (left). The behaviour driver model is placed at a higher level than the tactical level, this has several implications. Firstly, a driver's behaviour has an effect on all aspects of driving at the tactical level and filters down to the control level, also affecting that level. This relationship can be visualized is Figure 18 (right), the behaviour of the driver affects the tactical level and the control level. The affects of aggressive driving behaviour on the tactical level have already been mentioned, but the control level is also affected. The reaction time of driver that is fatigued or intoxicated will change the speed at which the driver reacts or how fast the he or she brakes.

Another aspect of this approach is that this simulation will be used to study accidents, which requires that all aspects of driver behaviour are incorporated into the simulation in order to make useful comments on how or why the crash occurred. As accidents are normally complex in the manner in which they came about, often no singular event in time is responsible, but rather a multitude of unfortunate events occur that eventually lead to a crash.

Another implication of this approach is that the tactical and control level in simulation terms can be seen as a layer of variables that are "driven" by the driver behaviour model. In terms of software engineering this means that the driver behaviour model can be implemented at a higher level and not directly in the tactical level, maintaining the modularity of MARS. Additionally this will allow the driver decision model to use existing interfaces and software already available in MARS (code reuse) with minimal or no changes to other parts of the simulation and keep the driver behaviour model simple and easy to implement. The tactical and control level will also not need to be modified and can be kept simple. The final advantage is that the driver behaviour model can be kept separate increasing portability for other simulation environments at TNO.

6.1.2. Conceptual model

Now that the driver behaviour model has been placed in context of the driving task and where it will reside within the MARS environment our focus can shift to the actual conceptualization of the driver behaviour model.

The driver decision model, containing perception and cognition, together form the driver behaviour model. Put otherwise the actions carried out by the driver model will display behaviour that is the result of various influences and factors, which can be analyzed. The conceptual framework will be kept simple and generic so that the underlying software design decisions and algorithm choices remain free.

Figure 19 shows a general overview of the driver behaviour model. There are two aspects to the model, the one half deals with the perception of the world surrounding the entity – the external factors - and how that data is processed. The decision model will receive sensory data. This data could be fuzzied by filters representing poor visibility for example. The perception unit will then process this data and pass it on. The decision model then processes this data and makes decisions based on it (internal half), resulting in actions that will be carried out. The chances of a particular action being taken based on statistics (age, gender and other human factors) and characteristics of the driver (aggressive, passive, fatigued, etc.) will result in actions.

The conceptual model (Figure 19) is an idealized version of how the driver behaviour model (DBM) should be structured and function. The undelying structure of MARS is not the most important consideration at this point (the structure of MARS was of course used as a basis).

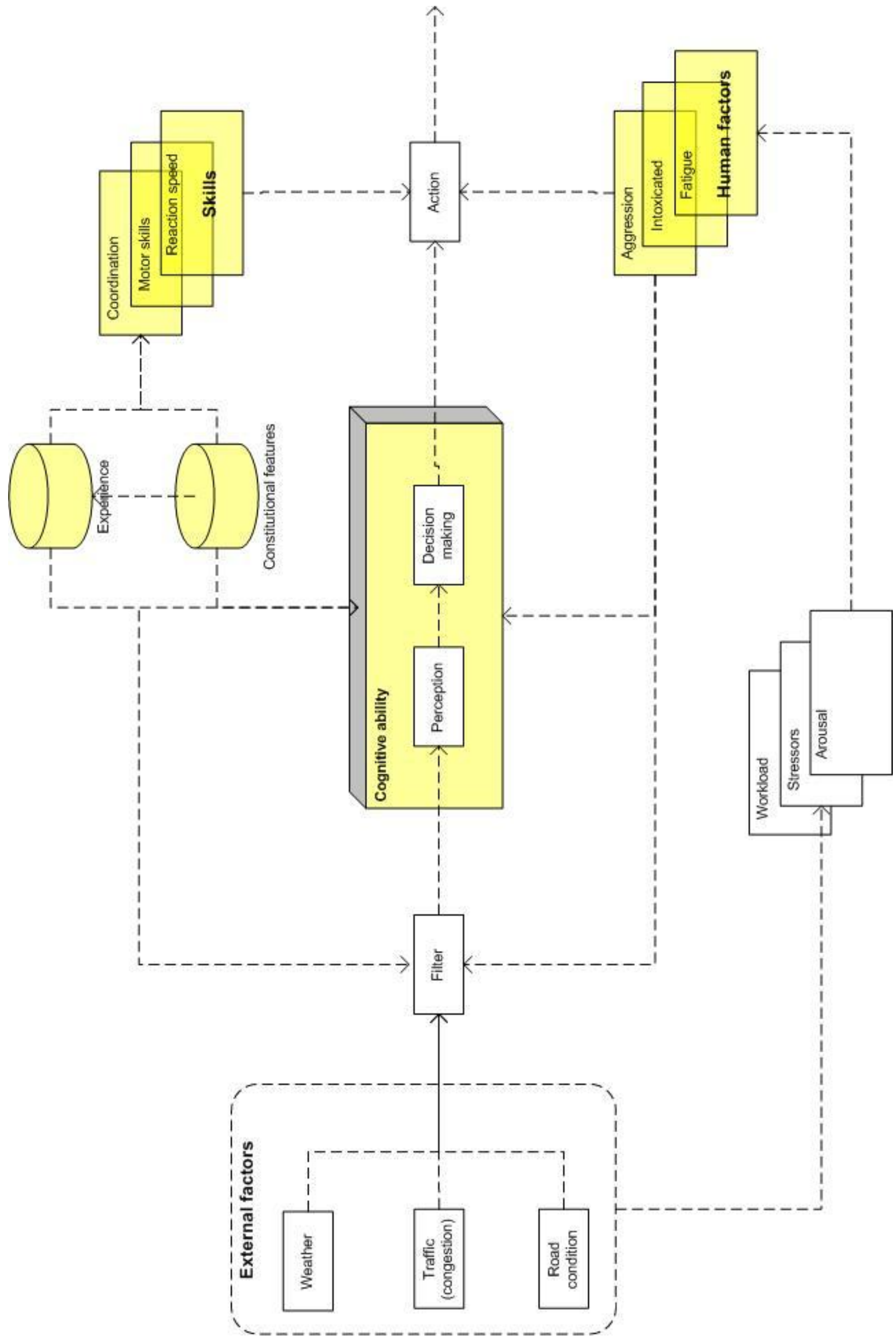

Figure 19 Conceptual model schematic.

This model can be viewed from two different perspectives. First the model has an internal and external division. There are external factors, such as the weather, traffic situation and road condition that affect the level of demand placed on the driver. There is also an internal part that represents the decision making processes made by the driver. Referring back to Fuller's model (Figure 10), with the division between the driver capability and driving task demand, this same division can be found in the conceptual model displayed in Figure 19. The top half of the model can be seen as the factors that define the capability of the driver, the lower half of the model is related to the demand on the driver.

6.1.3. Behavioural states

Several distinct driver behaviours, which will be referred to as behavioural states, have been selected and implemented in the DBM – namely: neutral, passive, aggressive, intoxicated and fatigued. To avoid any ambiguity or misunderstanding a behavioural state is defined as follows:

> A behaviour state is a condition (an emotional condition, mood or condition of fatigue or intoxication) that the driver finds himself in, that has a substantial effect on the way that the person drives.

The behavioural states that were selected for implementation in the DBM are neutral, aggressive, passive, fatigued and intoxicated. Each will be described in turn, detailing the effect that each state has on the driver.

Aggression

Aggression is defined as an emotion or mood that has several connotations associated with it. Aggressive behaviour is considered solely in the context of driving. There are several definitions of aggressive driving in traffic psychology, but the following definition will be used (Tasca):

> *A driving behaviour is aggressive if it is deliberate, likely to increase the risk of collision and is motivated by impatience, annoyance and/or an attempt to save time.*

This type of behaviour induces risk taking behaviour.

Neutral behaviour state

The neutral behaviour state can be seen as the control in the simulation experiment. This state is devoid of any behaviour. The state is neither aggressive nor passive and is risk neutral.

Passive behaviour state

The passive behaviour state is the exact opposite of the aggressive state. And it has a risk adverse nature, representing a cautious driver.

Intoxicated behaviour state

This state represents and impaired driver under the influence of alcohol, medication or drugs. Being in this state will result in greater perception errors and more erratic driving.

Fatigue behaviour state

A driver in this state exhibits behaviour that can be attributed to being overworked. Common effects of being fatigued while driving are lack of attention, poor vigilance and perhaps even falling asleep behind the wheel.

Summary of behavioural state
These behavioural states could be used to simulate various groups of the driver population. For instance, attributing aggressive behaviour to young, inexperienced male drivers that generally exhibit a more aggressive driving style. This has to do with the relative inexperience and overconfidence. However it should be noted that these kinds of generalisations are dangerous and often flawed. Using aggregate data to model an individual is asking for trouble, and is one of the fundamental mistakes that Michon warns against (Michon, 1989).

Each state has a unique set of consequences, their effect on what is called human factors. An overview of these effects can be found in Table 1.

Table 1 Simulation parameter modifiers for different behavioural states.

	Neutral	**Passive**	**Aggressive**	**Fatigued**	**Intoxicated**
Speed	speed limit	below limit	above limit	unaffected	erratic
Acceleration	normal	slow	fast	unaffected	erratic
Deceleration	normal	slow	fast	unaffected	erratic
Following distance	normal	large	close	unaffected	erratic
Gap acceptance	average	large	small	average	small
Risk	neutral	low	high	neutral	high
Error rate	none	normal	normal	high	high
Reaction time	normal	normal	normal	erratic	high

Each state and associated parameters are described in detail in Appendix A.

The error rate is used to simulated errors in perception, so that mistakes are introduced in judging distances or speeds of other vehicles and objects.

These behavioural states affect various parameters in MARS that are consulted continuously during decision making in the simulation. This method was chosen because it conforms with the idea expressed earlier that particular behavioural state affects the driving task as a whole and not only specific parts of decision making or perception.

The states are static in nature. The driver is in a particular behavioural state at the beginning of the experiment, this will not change during the simulation. Similarly, some parameters are set based on the age and gender of a driver. A dynamic component is also needed. This is where the concept of risk or difficulty can play a role.

6.2. Integration into MARS

With the conceptual model complete attention can now be turned to the actual implementation in MARS. Implementing the model in MARS requires the various elements of the conceptual model to be mapped to appropriate components in MARS. Constructing the DBM had several design considerations and constraints that will be addressed in the next section.

6.2.1. Constraints

The development of a driver behaviour model, specifically dealing with the integration into MARS, had the following design constrains:

1. The underlying architecture of MARS could not be changed.
2. The driver behaviour model should be loosely coupled to MARS.

The first constraint was set for several reasons. Firstly MARS has many different development branches and the developers of MARS are currently implementing a new version of MARS that will consolidate and merge these branches together. Parts of MARS that do not constitute the core architecture are continuously being improved and replaced, such as the visualization and experiment support modules. For these reasons the driver behaviour model can only extend the current architecture and not be completely integrated into MARS, so that new versions of MARS can easily upgraded with the driver behaviour model.

The most important contributor to these constraints is the future use and development of MARS. MARS is a generic framework, the controllers, detectors and devices represent a library of "plug & play" components that can be easily added to a vehicle platform so that experiments can be created and conducted. From a software engineering point of view this is an important consideration as it means that these components should remain as simple and generic as possible, leaving the complex individual behaviours to the DBM.

Keeping the controllers simple is important to achieving the goals of the DBM. The controllers represent the tasks and associated decisions necessary for carrying out manoeuvres and navigating in the simulation. As such these controllers should be kept simple and allow the DBM to add the non-homogenous and more complex behaviour to the entity. Implementing more complex behaviour directly into an individual controller would defeat the purpose of the DBM and create far more complex simulation environment. Maintaining the simplicity of the controllers and the basic MARS framework will greatly diminish the time required to setup and conduct experiments.

The development of experiments is a time consuming and often difficult task. Maintaining a simple and generic architecture means that experiment can be setup by simply plugging in generic components into the framework. For example, to create a simple experiment of cars that drive through an intersection a platform with the necessary devices, detectors and a simple controller that moves the vehicle from one point to another in the simulation would be added. A crossing controller could be added to those vehicles that will attempt to turn onto an intersection. At this stage already a simple experiment has been created, albeit with a homogenous in nature. Once the experiment is working as intended more complex behaviour can be added to the experiment using the DBM. DBM with tailored behaviours could be added to influence some of the drivers in a desired way. This simple, yet powerful approach is important to the future of MARS.

Some controllers have started to show significant code-bloat as engineers attempt to achieve more realistic and complex behaviours. This also shows the necessity of developing an extensible framework on top of the current MARS architecture capable of influencing driver behaviour. This will limit the creation of multiple slightly different controllers and devices that will only add to the general complexity of the simulation.

6.2.2. Design considerations

One of the main design obstacles that had to be overcome was the lack of detailed data. Data available for traffic simulations is often too general or too specific. Using data from other countries is not an option as the data can vary greatly between countries. TNO has detailed video footage, however this data was from highways and was not analysed with behaviour or safety in mind. Furthermore data from video footage will often not provide information about who was driving, such as the driver's age, gender and behavioural state. On the other hand experiments carried out on micro-simulation level usually require specific data that will be different for each experiment. The solution to this problem was to rely heavily on human factors engineering. Human factors such as average reaction time and effects of alcohol are based on empirical data. On average these factors will not vary across different countries. Additionally all factors that influence behaviour have been implemented in parameters that can be changed or calibrated easily without having to make changes to the software.

The design of the DBM was also made as light-weight as possible so as not to add to the already considerable computation time of MARS. Because each vehicle in MARS has its own decision making mechanisms the simulation is heavy on processor and memory resources. The design used here minimises the performance impact on the simulation.

6.2.3. Implementation

MARS is dominantly implemented in JAVA. Experiments are created in MARS using XML and JAVA (Simulink[1] can also be used to setup experiments, but the use of Simulink is being phased out). MARS was developed in JBuilder[2] 2005. The Eclipse[3] integrated developer environment was during this project to implement the DBM.

Implementation of the DBM into MARS was relatively easy because it is well designed and programmed. The design is modular, flexible and expandable. Moreover the source code is neat and well documented.

There are basically three different ways to influence the decision making process in MARS, specifically the decisions made by controllers such that behavioural aspects can be introduced into the simulation.

The first option was to change the controllers by directly adding behaviour. This however would result in the controllers not being generic and would require reprogramming of many of the controllers. This option was rejected immediately as it also violates the first constraint (that MARS should not be altered). Secondly, a driver's behaviour should influence all decision making process, not just a few. If each controller has its own behaviour there is also a chance that the global behaviour could become inconsistent.

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[1] Simulink - https://tagteamdbserver.mathworks.com/ttserverroot/Download/43815_9320v06_Simulink7_v7.pdf

[2] JBuilder 2005 - http://www.borland.com/resources/en/pdf/products/jbuilder/jb2005_feature_matrix.pdf

[3] Eclipse IDE - http://www.eclipse.org/

Next altering the suggested actions generated by the controllers was considered. This would involve intercepting and changing the suggested actions produced by controllers before passing the suggestion on. The behaviour mechanism would not really influence the actual decision making process, just change it. The same decisions would always be made by an individual controller regardless what the behaviour of the driver was. This approach would lead to decision simply being modified or discarded. This option was also rejected, in part because it would not be an easy mechanism (to intercepting the suggested actions and place them into the correct context) to implement and would require adding extra layers to MARS.

Finally it was decided that the easiest and most efficient (computationally) would be for observers to monitor controllers. This only required that the controllers extend a subject class, which has generic reporting methods. When important information, such as state changes in the controller occurs, a simple notify method could be called which would automatically inform interested observers that the controller has new information. The new information could then be considered and appropriate changes made to the settings file before passing execution back to the controller. In this non-invasive method the actual decision making process of the controllers is manipulated by changing parameters in the settings file that the controller continuously consult in order to make decisions. This realistic and effective method was also the most simple of the three solutions to implement. This method also conforms to the conceptual model.

From a software engineering point of view there are several concerns. First and foremost is the lack of detailed data for calibration and validation. To address this concern the underlying modules that make use of this data will have to be modular, so that when new data becomes available, better algorithms and statistical models can easily replace the current ones.

Figure 20 shows an overview of the MARS entity (in orange) with the DBM (in blue). Each MARS entity has its own DBM, with its own behavioural state, unique characteristics and internal logic. The DBM extends the basic MARS entity by adding behavioural aspects.

The DBM monitors the state of controllers using a simple observer design pattern. All controllers extend the *Subject* class that contains notify methods that update all the *Observers* that are interested in a particular controller. When an observer has a notification about what has changed in the controller the DBM consults its own internal logic, kept in the *DBM* class, and may modify the settings file that the controller consults to make decisions. In this simple way the DBM can influences the entities decision making process.

The *PerceptionUnit* deals with the perception and has access to a list of objects that the detector has seen in the surrounding world. The PerceptionUnit can alter information about these objects, for instance the distance of the object, which can be used to emulate misjudgements on how far away the object actually is. An alternative method is to do this through observers, as controllers generally also have access information on objects in the world (which they use to make decisions).

The *DriverProfile* class is a wrapper for the *Settings* class, extending the *MyPreference* class. DriverProfile class protects the DBM module from changes in the settings class. The

DriverProfile class also adds additional settings that are unique to the DBM module. At some point these extra settings may be merged into the MARS settings file. The *DBMPlatform* extends the original Platform class, allowing the original MARS entity to be created using this class as well. Besides allowing specific DBM parameters to be added the DBMPlatform also protects the module from changes in the rest of MARS.

The behaviour class contains the behaviour states along with the parameters associated with each state. Modification or the addition of a new behavioural state can be done in a single class.

The DBM also has a logger that allows information specific to the DBM to be gathered for research and debugging purposes. This logging system can be merged into the MARS logger, but was kept separate so that the DBM could remain independent.

This structure insures that the DBM is flexible and transparent. The implementation has kept the DBM independent from MARS and no major changes to the architecture of MARS were required. The DBM can be easily added to any existing MARS entity.

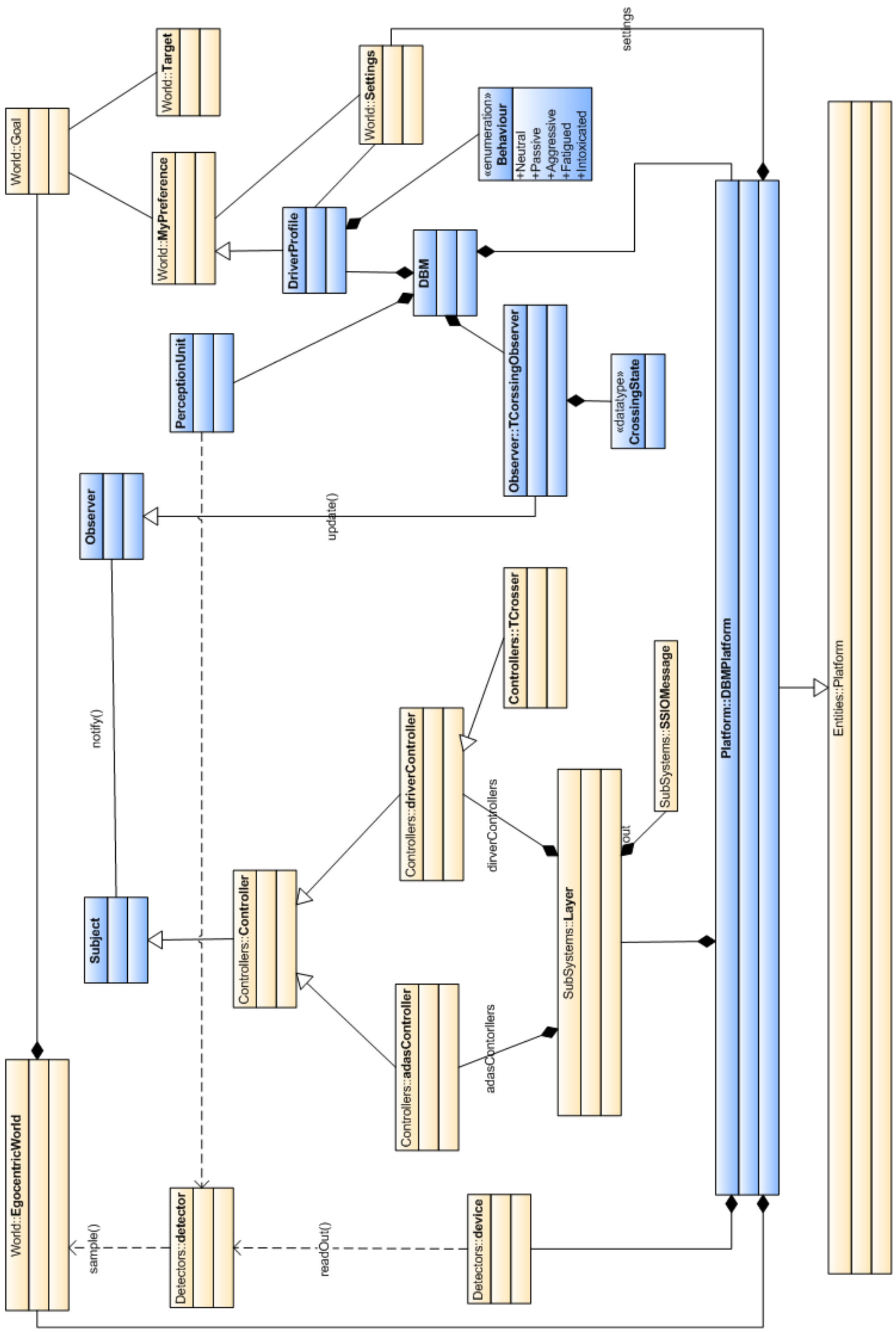

Figure 20 UML diagram of the DBM extension of the MARS entity.

Chapter

7

7. Simulation and Results

In this chapter a proof of concept that was implemented to test the new DBM in simulation is presented.

7.1. Proof of concept

A proof of concept model was implemented to demonstrate the use of the DBM. The proof of concept extends an intersection crossing controller. The crossing controller was created by Tim van Dijk for his research into gap acceptance at intersections (van Dijk, 2008). This controller encapsulates the decision making logic necessary to successful execute left turn entry into the main flow at a T-junction. This situation is shown in Figure 21.

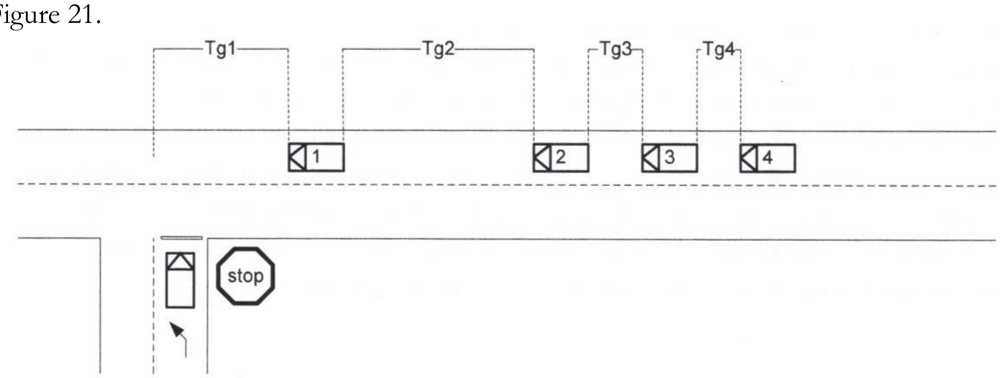

Figure 21 Left hand turn entry into main traffic flow (van Dijk, 2008).

This gap acceptance model also takes into account multiple gaps when deciding whether or not to accept a give gap. The controller looks at up to four gaps (Tg1, Tg2, Tg3, and Tg4). The each of the gaps has a weighted score: 1.0, 0.75, 0.5 and 0.25 respectively. The gap farthest away receives has the lowest weight. The basic idea is that a driver will pass on a relatively short gap (Tg1, directly in front of the driver) in favour of another gap down the flow if that gap is larger (i.e. one of the oncoming gaps will receive a higher score). The crossing controller considers traffic from coming both sides and joins them together forming one array of gaps.

This particular controller is a perfect candidate to use the DBM. This controller is much larger than other controllers in MARS, approximately 5 times larger (in lines of code) than an average controller. The controller does execute a relatively complex manoeuvre requiring additional logic and therefore needs more lines of code, but the controller is none the less suffering from code-bloat to a degree. By using the DBM there is a choice to move the logic required to decide which gap to accept to the DBM. This would lower complexity and make the crossing controller more generic.

In this experiment the crossing controller was left completely unchanged. Van Dijk originally planned to add another dynamic to the crossing controller that would lower the size of the gap that the controller would accept based on waiting time. Unfortunately there was not enough time. This concept is based on the idea that the longer a driver waits the more impatient the driver will become, resulting in acceptance of shorter gaps.

> *Assumption: The longer a driver weights the smaller the gaps he will accept become (van Dijk, 2008), (Pollatschek, Polus, & Livneh, 2002).*

An observer was implemented that watches the state that the crossing controller is in. This observer receives updates on state changes in the crossing controller and based on this information it dynamically changes the size of gap that the driver is willing to accept. The crossing controller will only accept gaps that are larger than its critical gap size, which is stored in the entities settings file. The observer dynamically changes this critical gap size, based on how long the vehicle waits. The advantage of this method is that the crossing controller itself remains unchanged, not one line of source code needs to be changed (only a simple notify method call need to be added).

The model uses the notion of risk (of an accident occuring) and the impatience (waiting time) to dynamically affect decisions. The waiting time is seen as a penalty for not accepting a particular gap. The risk represents resistance to accepting gaps (very shorts/small gaps in the traffic) that have a higher likelihood of causing an accident. The risk model used is based on model developed by (Pollatschek, Polus, & Livneh, 2002). The model uses a simple risk function:

$$r(t) = \begin{cases} \infty & t \leq t_{sa} \\ c\,(t - t_{sa})^{-\alpha} & t > t_{sa} \end{cases} \tag{1}$$

Where t is the size of the observed gap in sec, c is a parameter for the cost of time, t_{sa} is a gap size below which an accident is sure to happen (t_{sa} = 3.0 seconds for this experiment) and α is risk parameter. A small value of α corresponds to a risk-seeking driver and large α represents a risk-averse driver. If the observed gap, t, is smaller or equal to t_{sa} the risk is infinite (because a crash is certain).

A plot of the risk function (1) is shown in Figure 22.

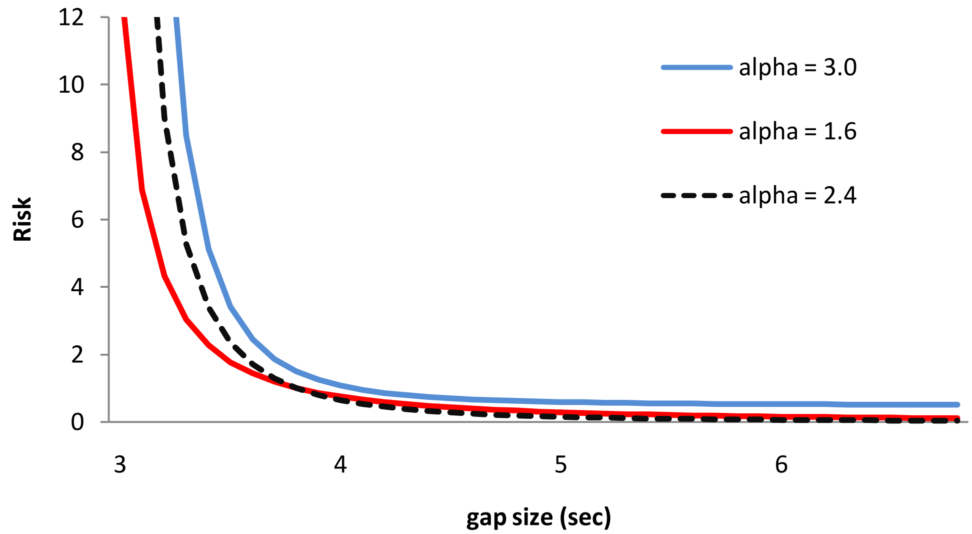

Figure 22 Risk functions.

The model makes a basic assumption that there are people who are risk loving (risk-seeking) and those that attempt to mitigate all risks (risk averse). This assumption is based on economic theories dealing with investments. In the choice of portfolios some investors will choose risky investments, while others will diversify and choose safer investments to mitigate risks (Levy & Sarnar, 1986).

The method used by (Pollatschek, Polus, & Livneh, 2002) to model the size of gap to accept and the modification of critical gap size is based on a passion process that models the intensity of traffic on the intersection. The critical gap is changed using a Bayesian estimator. In order to keep the model simple a modified version was used that does not require exact knowledge of traffic intensities. The risk function shown in (1) was used. To be able to relate risk to the time a driver has waited the risk function must be expressed in a monetary equivalent. Details can be found in Appendix B. The risk is now expressed in seconds and is commensurable with waiting time.

The Figure 23 shows the relationship between risk and waiting time.

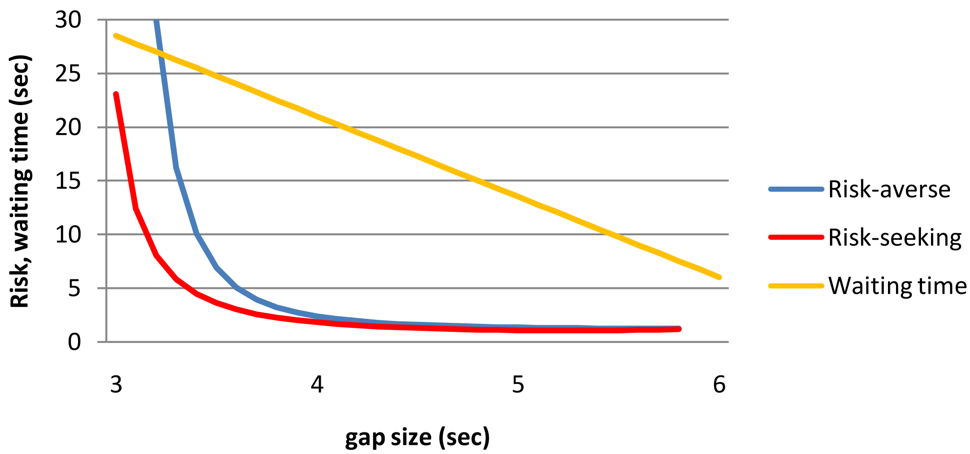

Figure 23 risk related to waiting time in terms of gap size.

Figure 23 relates risk to waiting time. The longer a driver waits the shorter the gap size will become as the driver become less patient and accepts a higher level of risk. The closer the driver's critical gap comes to t_{sa} (3 seconds gap size in Figure 23) the higher the risk of an accident becomes. It is also assumed that the driver will not wait much longer than 30 seconds. The model is easy to adapt as the model is based on only a few parameters. A gap of 6.0 seconds is considered to have no risk associated and the driver will go. A risk-seeking driver will accept a shorter gap sooner than a risk-averse driver.

Based on this relationship and risk the critical gap is shortened as waiting time increases. The DBM receives notifications on the current state that the vehicle (controller) is in. The observer keeps track of how long the driver has been waiting at the intersection and dynamically changes the critical gap of the controller. Eventually after waiting some time the critical gap is small enough that a gap can be accepted and the vehicle can make the left turn entry.

For this experiment a simple traffic flow was used with continuous and constant gaps of 3.5 seconds in size. When the vehicle arrives at the intersection the critical gap is initially set to 6.0 seconds. The experiment setup is shown in Figure 24.

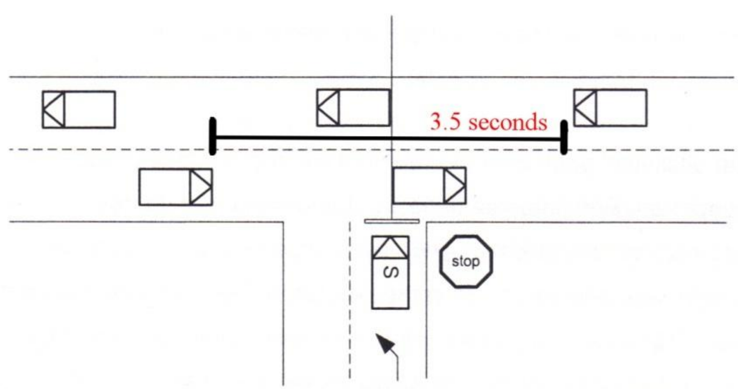

Figure 24 Experiment setup.

Two drivers were used, a risk-seeking driver (α = 1.6) and a risk-averse driver (α = 3.0). The results of the experiment are shown in Figure 25.

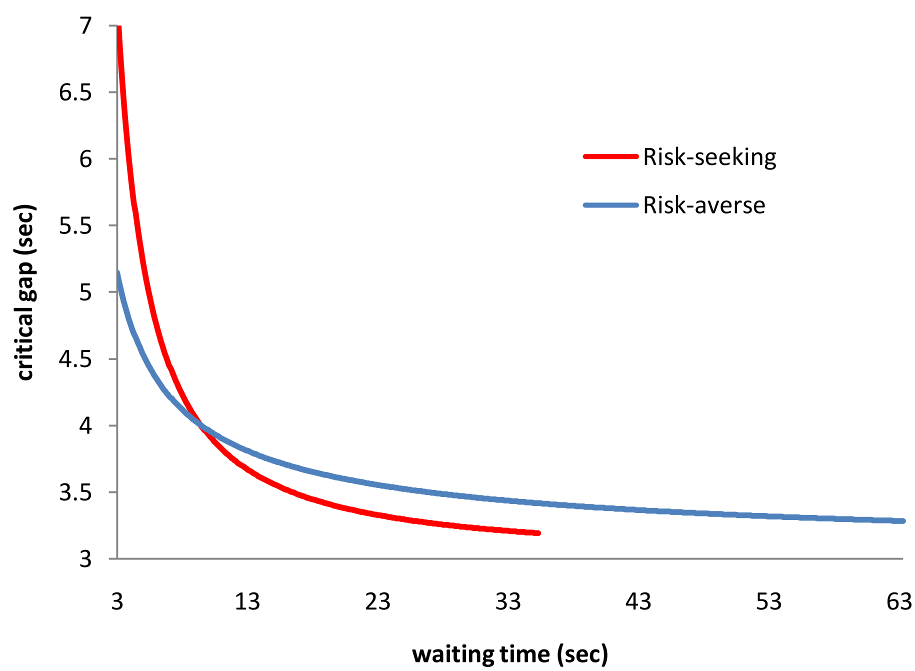

Figure 25 Experiment results, waiting time and critical gap.

Initially (after 3.0 seconds of waiting) the risk-averse (in blue, Figure 25) driver has a smaller critical gap this is due to the risk function that was used (which was chosen for its simplicity). After a waiting another 3.0 seconds the critical gap of the risk-seeking (in red, Figure 25) driver decreases faster than the risk-averse driver. The risk-seeking driver carries out his left turn after 35 seconds of waiting. The risk-averse driver hower waits nearly twice as long be turning onto the main road. Both driver will not accept gaps smaller than 3.0 seconds as this is the value of t_{sa} in the experiment.

7.2. Results and model test

The gap acceptance model controller was easily extended with dynamic gap size reduction based on waiting time and risk. A more complex and accurate model could easily be implemented using the model described in (Pollatschek, Polus, & Livneh, 2002). The only addition that was made to the crossing controller was the addition of one line to update the DBM on the status of the controller. The DBM does affect or override the basic functionality of the MARS controller. The crossing controller still considers multiple gaps in its decision. The only difference is that the critical gap of the controller, which was static, is now dynamic.

The experiment was easy to implement using the DBM and demonstrated the strength of this approach. The behavior of the driver, risk-seeking or risk-averse, was expressed using the aggressive and passive behavioural states. The implementation of this proof of concept also creates a more realistic gap acceptance model for MARS. Gap acceptance is a critical maneuver and an important area of traffic safety analysis as this is one of the more complicated and accident prone manuevers.

The model was verified visually and using a reference model. The reference model was first created in excel and was used to calibrate the model. The experiments were then carried out in the simulation. The logged data was then compared to the reference model to confirm that the model was operating as predicted. The simulations were also visually inspected to insure that no unexpected or erratic behaviour occurred. The vehicles in the simulation correctly did not enter when the observed gap was smaller than t_{sa}. The vehicle also did not wait when the observed gap was larger than the current critical gap size. The experiment was compared to the normal functionality of MARS and Tim van Dijk's model to insure that the DBM functioned properly and as expected.

The experiment was also carried out with a more realistic traffic intensity, which was also used in van Dijk's experiment. The experiment uses a Erlang(2, μ) distribution which is a special case of a gamma distribution. This distribution provides a realistic arrival rate of vehicles on the intersection. The DBM performed properly in this case as well.

Implementation of this proof of concept, behavioural states and experiment were used to test and debug the software to insure that the simulation functioned properly. System debugging information is included in the logging system and the real-time simulation output. JAVA asserts were used and system exit functions were included to halt the simulation when undesired conditions or errors occur. It should be noted that the correctness and proper functioning of the DBM dependent on the underlying MARS architecture, which were assumed to be correct.

Chapter

8

8. Conclusion

In this chapter a conclusion is presented, along with recommendations.

The ultimate goal of this research was to develop and implement a drive behaviour model in the Multi-Agent Real-time Simulation, so that more realistic experiments can be carried out for the purpose of traffic safety analysis. A driver behaviour model has been designed and implemented which creates more realistic driving behaviour. In order to achieve this goal several key questions had to be answered, will now be discussed in turn

Which psychological model is best suited for implementation into a traffic simulation?

> The selected psychological model by Fuller is a satisfactory framework in which the decisions made by drivers can be considered. The model lends it self well to implementation in a computer model as it can be made concrete. Regardless of the actual mechanism that "drives" the decision making based on subjective risk or difficulty was not the determining factor to use this particular model. The strength of Fuller's model lies in the use of what he calls constitutional features and human factors. While trying to implement psychology in software is inherently difficult and fraught with problems, human factors in comparison are well suited to implementation in software, as the factors based on responses, reactions and errors that can be measured and set as parameters in the simulation. The framework can easily be adapted if new or more concrete empirical evidence is found.
>
> A consistent and coherent structure has been implemented that adheres to Michon's guidelines. There is a clear separation between the functional level (MARS) and aggregate behaviours (DBM) that influence the functional level.

What are the key factors and behaviours that influence driving and safety?

> Key factors affecting driving were identified and combined into behavioural states. The key behavioural states were aggression, passive, neutral, fatigued and intoxicated. Each state has a human factors associated with it in a unique way. These behaviours have the most dramatic effect on how a driver behaves and on safety measures. The flexibility of the states within the DBM means that the states can be modified and new states can easily be added.

The implementation of moods or behavioural profiles such as aggression, intoxication and fatigue are abstract and difficult to quantify for the purposes of simulation. Although in the case of aggression, which is an observable behaviour that has direct effects on driving behaviour is interesting. Many of these moods that affect the level of risk while driving can be translated into theories such as economics, in particular investment strategies. We know that some individuals will select investments with a higher level of risk versus others that will allocate a portfolio that mitigates risk. I believe that these sort of assumptions are not perfect but do provide a working hypothesis that can be applied successfully in simulation.

How will driver behaviour be transformed and integrated into the Multi-Agent Real-time Simulation?

The integration and implementation of the DBM into MARS had some strict constraints. Not being able to change the underlying structure of MARS was a challenge, but the resulting framework works well. Extending MARS with the DBM, while leaving the core of MARS unchanged, will result in a framework with simple and generic components. This will greatly aid future development of MARS.

The use of risk in Fuller's model, based on Wilde's theory of risk homeostasis has received a lot of criticism and been drawn into question (Vaa, 2001), (Michon, 1989). During this research and particularly during the implementation of the model it was found that it was impossible to implement a general risk function that affect all the decisions made by drivers. This was largely due to the way that MARS is structured with controllers making independent specific decisions related to the driving task. It is not likely that generalized risk function or homeostat that affects all the decisions can be implemented. Rather a risk function can be implemented for specific decisions or a set of decisions, such as whether or not to accept a gap. The driver always has to accept a certain amount of risk which is inherent in driving, but it is better to model risk in each specific case. Risk is often associated with the variances in perception or estimations made by drivers and the cost of these risks are calculated based on mistakes made in the estimates that lead to incorrect or inaccurate decisions. These functions, especially in a simulation dominated by parameters and calculations, are impossible to define in a generalised way.

The DBM is based on generally accepted human factors that are based on empirical and aggregate data. The model will require "tweaking" as is always the case when carrying out detailed and accurate experiments in a simulation environment. The design of the DBM deals well with the lack of detailed data on human behaviour by providing flexibility. As more experimental data becomes available the data can be used to improve the DBM. Practically all human factors in the DBM are simple parameters and can therefore be easily modified.

A proof of concept was implemented based on the gap acceptance model (van Dijk, 2008) proving the versatility of the model. The results show how dynamic aspects of behaviour can be incorporated into the decisions made by drivers. The DBM influences the decision making processes of drivers without the need to alter the underlying decision making components, thereby maintaining the simple and generic structure of MARS.

The model reduces complexity of the underlying MARS architecture and provides a more realistic simulation that is capable of carrying out detailed research in a multitude of areas. More realistic driving behaviour will not only provides better safety analysis but can also be used for capacity research on intersections and for emission models. Because of MARS robustness conducting experiments on emissions, for instance, will only require the addition of logging information. The framework also provides a platform to test advanced driver assistance systems in a realistic environment.

Modelling a human being is inherently difficult, if not impossible and I have tried, to "steer" away from attempts to implement a complete human. Instead the goal of this project was to model an aspect of human behaviour and the effects a particular (or combination of behaviours) has on the associated decision making specifically during driving only and the resulting affects on safety and other facets of driving.

8.1. Recommendations

During the development of the DBM numerous interesting areas of research were discovered, many however fell outside of the scope of this project. Nevertheless because of the importance of this research and the benefits these areas potentially hold, some of these will be discussed here. These issues constitute promising additions to the DBM and MARS that should be considered in further development of the simulation.

An important aspect of driving safety is distraction or inattention, which can be caused by a work overload, fatigue or under arousal. Distraction is one of the most difficult factors to simulate. MARS at the current time does not have an accurate enough model of a human being for distraction to be properly implemented. The question is when does the driver become distracted and what is the result of being distracted. Being distracted could result in a driver not sensing an important event or another vehicle on time or completely missing the event all together. Since distraction plays an important role in accidents efforts should be made to develop a mechanism to incorporate it.

A related issue to inattention and distraction is workload. There is no clear way to do this in MARS, several possible ideas were considered. Using the level of contention, defined as the number of conflicting suggested actions produced by the controllers as a possible value for Fuller's difficulty homeostasis model. Perhaps controllers and associated decisions can be used as a relative measure of difficulty or disharmony in a particular situation. Theoretically the amount and level of contradictor suggested actions can indicate that a driver is in a difficult or complex situation that requires extra consideration. The more complex (or "difficult") a situation is then theoretically there should be a higher level contention. Another possibility is to use the number of active controllers (controllers are not always active) and the number of objects that the entity is tracking at time as measure of workload. This could be modelled as the working memory of the driver. The next question then is what to do if a work overload is detected. Should some objects being tracked be ignored or lost and which object should these be. These are difficult questions that will hopefully be addressed in the future.

The calibration and validation of the model is problem because that there is not enough detailed data. It is questionable whether video data alone will be sufficient. From video footage it will not be possible to ascertain who was driving the car, leaving us to guess the characteristics of the driver were (age, intoxication or fatigued, etc.).

Concrete and detailed data on drivers, of a particular age, gender and level of experience should be gathered for specific situations (various intersections, particular roads with different levels of congestion and traffic intensities) and used to calibrate and improve the model. This would go along way towards creating a more realistic and accurate simulation. The best method for obtaining this data would be by either carrying out real driving or simulator experiments. At the same time it should be strenuously stated that the experiments should be carried out with drivers making up a diverse part of the driving population, there should be several drivers from different age groups and gender. The drivers should also fill out questionnaires afterwards to ascertain the subjective side of the driving experience (difficulty level, mood and other behavioural information). This data can then be incorporated into the DBM.

Because the model is based on a psychological model at its core it will be difficult if not impossible to validate the model completely. Faith will have to be put into the correctness of the psychological model used. However since the model relies heavily on human factors, that can directly measured there is an inherent level of confidence in the model. An important consideration is whether all important factors that influence driving behaviour have been included in the model. The most important and directly observable behaviours have been included, however factors relevant to these behaviours such as distraction or inattention are very important and should be include at some stage.

An advantage of the model is that by carrying out concrete should automatically improve and calibrate the model. Most experiment focus on particular aspects of driving that require detailed data. The better the data used in the experiments the better and more reliable the model will become.

Another area that is very difficult to model is the effect of experience. It is clear that experience has a definite effect on driving performance, but making this relationship concrete in the form of simulation parameters is not possible at the current time, due to lack of available data and understanding how experience directly effects driving. However given the importance of experience as an important factor that influences driving and traffic safety efforts should be made to understand and implement the influence into the simulation. It is quite possible that experience "hides" and can only be observed by the affect it has on other factors. For example, experience can increase reaction time because the driver expects certain events to happen based on similar situations that the driver has encountered before. Modifying parameters in the simulation to reflect this mechanism is a possible solution.

The behavioural states are static (there are no behavioural state transitions during the simulation). The state of a driver is set before the simulation starts, however the states were implemented in such away that the behaviour of a driver can change. Dynamically changing the behavioural state of a driver was not pursued further because the experiments conducted in MARS usually focus on an intersection or short piece of road, so that each vehicle is in the simulation for a very short time (not enough time for a drivers behaviour to change noticeably). Detecting what circumstance cause a driver to shift to a particular behaviour is problematic. An interesting field of research was uncovered during this project dealing with what triggers aggression and how the drivers responded (Lajunen & Parker, 2001). This research used a statistical inference method know as path analysis and may be interesting in the further development of MARS.

8.2. Personal perspective

I have enjoyed studying human factors engineering and psychology in the area of traffic safety. This project was ambitious in its scope, essentially attempting to model a human being, albeit in a specific situation. Most attempts to model human behaviour have been met with limited success.

At the very least this research will provide TNO with a driver model that can be used to analyse safety. In the simple event of two cars meeting at an intersection there are an extremely large amount of possible outcomes even for such a relatively straight forward scenario. This large amount of uncertainty will enable TNO to test their advanced driver assistance systems and adaptive cruise control in a realistic environment. It is impossible for anyone person to analytically calculate or oversee all the possible outcomes or results of human behaviour for such a complicated system like the traffic system.

I have tried to limit the scope of the project, hopefully without sacrificing any important factors. The project has significant scientific and practical applications in the important area of road safety in which we all have a vested interest.

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Appendix

A

Appendix A: Behavioural states

In this appendix provides an overview of the parameters associated with each behavioural state in greater detail.

Each of the behavioural state will be described in detail. A detailed overview of each behavioural is provided, with specific values for each parameter and sources (if applicable). The error rate refers to errors made in perception, specifically errors in judging distances and speeds of other vehicles and objects.

Neutral state

The neutral state is the state devoid of any behaviour. An entity in the neutral state drives without any affect from the DBM. All other states are described relative to this state. This state has a risk-neutral behaviour. The parameter for α is set to a value that is in between risk-seeking and risk-averse.

Table 2 Detailed overview of parameters for the neutral behavioural state.

	Effect	Source
Speed	Speed limit	
Acceleration	normal	
Deceleration	normal	
Following distance	normal	
Gap acceptance	$\alpha = 2.4$	(Pollatschek, Polus, & Livneh, 2002)
Risk	Risk-neutral	
Error rate	none	
Reaction time	normal	

Aggressive state

The following of aggression is used (Tasca):

> *A driving behaviour is aggressive if it is deliberate, likely to increase the risk of collision and is motivated by impatience, annoyance and/or an attempt to save time.*

Although literature concerning aggressive driving states that exceeding the speed limit in one of the visible effects there is no definitive measure (percentage) how far above the speed limit aggressive drivers generally drive. For this reason the speed, acceleration and deceleration will be set to 10%, which can be easily changed (data on specific road ways and intersections will yield a better estimation in each particular case).

Aggressive driving is considered a form of risky driving and will therefore be associated with a risk-seeking behaviour. Aggressive driving has no effects on the error rate or reaction time. Table 3 provides an overview of the parameters used for the aggressive behavioural state.

Table 3 Detailed overview of parameters for the aggressive behavioural state.

	Effect	**Source**
Speed	10 % above limit	(Tasca)
Acceleration	10% faster	
Deceleration	10% faster	
Following distance	50% of normal	
Gap acceptance	$\alpha = 1.6$	(Pollatschek, Polus, & Livneh, 2002)
Risk	risk-seeking	
Error rate	normal	
Reaction time	normal	

Passive state

The passive state is defined as being opposite to the aggressive state. This state corresponds to a cautious driver and is risk-averse. Like the aggressive behavioural state there are no affects on the error rate or reaction time.

Table 4 Detailed overview of parameters for the passive behavioural state.

	Effect	Source
Speed	10 % below limit	
Acceleration	10% slower	
Deceleration	10% slower	
Following distance	50% of normal	
Gap acceptance	α = 3	(Pollatschek, Polus, & Livneh, 2002)
Risk	risk-averse	
Error rate	normal	
Reaction time	normal	

Fatigued state

This state represents a driver that has become fatigued and no can no longer operate at an optimal level. Fatigue diminishes the driver's cognitive ability, which affects the driver's reaction speed (Li, Jiao, Chen, & Wang, 2004) and perception (increasing the error rate). The speed driven by the driver will be erratic as the driver struggles to concentrate and maintain a constant speed. This state had no effect on the level of risk accepted by the driver.

Table 5 Detailed overview of parameters for the fatigued behavioural state.

	Effect	Source
Speed	erratic	
Acceleration	normal	
Deceleration	normal	
Following distance	normal	
Gap acceptance	α = 2.4	(Pollatschek, Polus, & Livneh, 2002)
Risk	risk-neutral	
Error rate	high	
Reaction time	increased by 20%	(Li, Jiao, Chen, & Wang, 2004)

Intoxicated state

This state is associated with the impaired driver, specifically a driver with alcohol intoxication. The effect of drugs will not be considered because different drugs have different effects on driving. Alcohol affects the forebrain by suppressing caution, carefulness, concentration, self criticism and self control (South African Department of Transport). The lack of caution exhibited by intoxicated drivers increases the level of risk taken.

Alcohol has an effect on perception. Depth perception is depth perception making it difficult to correctly judge how far away an object is (Wright State University). At moderated blood alcohol levels perceptual speed is also affected (Jones, Chronister, & Kennedy, 1998).

Alcohol also has a significant affect on reaction time. Figure 26 show the effect of alcohol on reaction time. There is a linear relationship indicating that reaction time under the influence of alcohol increase by approximately 30%.

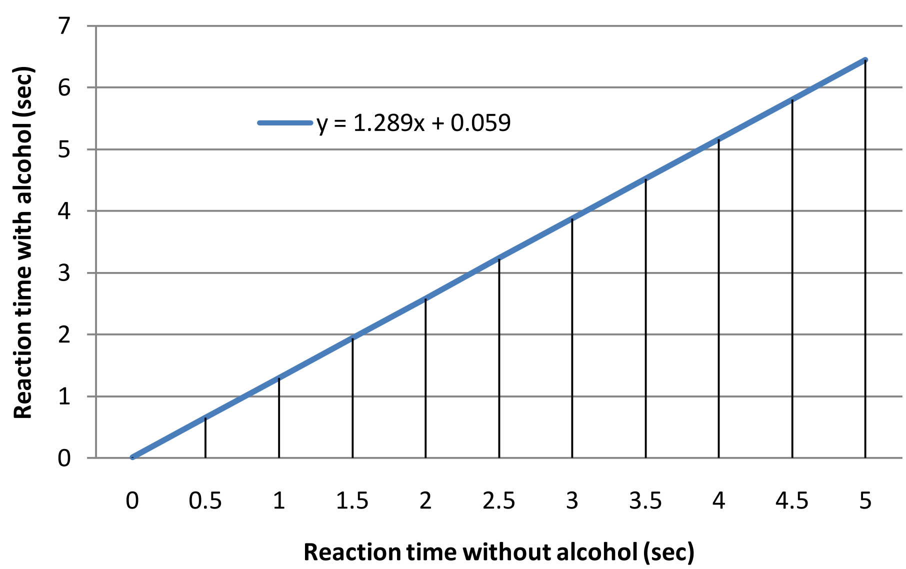

Figure 26 Affect of alcohol on reaction time (Caird, Lees, & Edwards, 2005).

Figure 26 is based on a best fit for three difference blood alcohol concentrations (0.01-0.049; 0.05-0.079; 0.08-0.10). The fit equation accounts for 98.87% of variance in the data included (Caird, Lees, & Edwards, 2005).

Intoxicated drivers are unable to maintain a constant speed while driving, either driving too fast or slow. Starts and stops are also jerky (Pennsylvania Department of Transportation).

An overview of all parameters used in for the intoxicated state are shown in Table 6

Table 6 Detailed overview of parameters for the intoxicated behavioural state.

	Effect	Source
Speed	erratic	(Pennsylvania Department of Transportation)
Acceleration	erratic	
Deceleration	erratic	
Following distance	erratic	
Gap acceptance	$\alpha = 1.6$	(South African Department of Transport)
Risk	risk-seeking	(South African Department of Transport)
Error rate	high	(Wright State University)
Reaction time	increased by 30%	(Caird, Lees, & Edwards, 2005)

Appendix

B

Appendix B: Experiment setup

In this appendix provides an overview of the model used in this research and simulation experiment.

The risk model used is a simplified version of the model used in (Pollatschek, Polus, & Livneh, 2002). The model uses the following function to calculate the risk of accepting a particular gap size. This risk function is shown below.

$$r(t) = \begin{cases} \infty & t \leq t_{sa} \\ c\,(t - t_{sa})^{-\alpha} & t > t_{sa} \end{cases} \tag{1}$$

Where t is the size of the observed gap in sec, c is a parameter for the cost of time, t_{sa} is a gap size below which an accident is sure to happen (t_{sa} = 3.0 seconds for this experiment) and α is risk parameter. A small value of α corresponds to a risk-seeking driver and large α represents a risk-averse driver. If the observed gap, t, is smaller or equal to t_{sa} the risk is infinite (because a crash is certain).

The risk function was calibrated in excel before running the experiment. The model uses the following parameters to calibrate the model:

- waiting time (W)
- t_{sa}
- c
- t_{nr} - a gap size where the risk is negligible

These are the only parameters need to calibrate the model. The waiting time selected was 30 seconds. The calibration of the model involved adjusting the risk value, $r(t)$, so that it was comparable to the waiting time. This meant finding an acceptable value for the cost of time (a value multiplied the cost per second for waiting) and an appropriate value of c so that the weighting time would be close to the risk of accepting a gap close to t_{sa} when the weighting time reached 30 seconds. Based on the time weighted, which is commensurable with the risk, the critical gap size was altered to the value of in the t in the function $r(t)$. In other words, after waiting a particular amount of time a certain amount of risk is accepted, for which there is a particular value of t (gap size). This value is then used as the new critical gap value (the minimum size of gap, in seconds, that the driver is willing to accept). In this way the longer the driver waits the shorter the driver's critical gap will become (until reaching t_{sa} after which the critical gap can become no smaller).

To test this risk base gap acceptance model a simple experiment was setup as follows:

- A car, *S* in Figure 26, arrives at the T-junction intersection attempting to execute a left hand turn to enter the main traffic flow
- Car *S* starts the experiment upon arriving at the intersection with a initial critical gap of 6.0 seconds
- A continual, constant flow of cars travel over the main road, from both sides.
- The combined gap between two (one from the left and one from the right) cars approaching the T-junction intersection is 3.5 seconds long (as is marked in red in Figure 27).

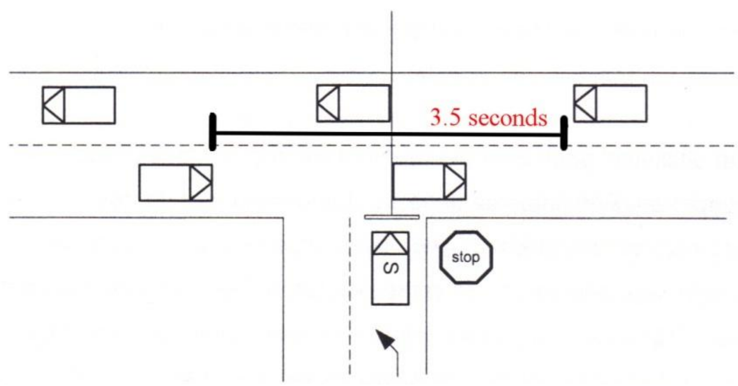

Figure 27 Experiment setup.

In order for car *S* to execute the left hand turn the critical gap must first decrease to below 3.5 seconds (this is time between each consecutive gap on the main road).

This experiment was carried out using two values of α. 1.6 and 3.0 respectively, that represent a risk-seeking and risk-averse drivers.

The results of the experiment were compared to the expected values obtained from calculations made in excel based on the calibration of the model.