Modelling car driver informing and route choice under uncertainty about DRIP travel times

Master Thesis Report

Jayant A. Ramautarsing
August 2011

Student number: 1115030
University: Delft University of Technology
Faculty: Civil Engineering & Geosciences, Section T&P
Master: Transport, Infrastructure & Logistics

Graduation Committee
Prof. dr. ir. B. (Bart) van Arem – Section Transport & Planning – Chairman
Dr. ir. A. J. (Adam) Pel – Section Transport & Planning – 1st Supervisor
Dr. ir. C. (Caspar) Chorus – Section Transport & Logistics, faculty TPM – 2nd Supervisor TU Delft
Dr. M. (Martijn) van Noort – Supervisor TNO
Dr. M. (Maaike) Snelder – Supervisor TNO
Summary

Travel and traffic information play an important role in traveller behaviour and traffic flows. Travellers have the possibility to use information on current and future traffic situations to make their travel decisions. Travel decisions by individual travellers subsequently influence the performance of a total traffic system. This makes behaviour of travellers an interesting topic to policy makers and road operators. In this thesis travel choice behaviour also plays a central role and we specifically take into account car drivers and en-route route choice.

This graduation assignment was done at TNO and after an initial scope further focus was applied resulting in the goal of modelling driver traffic information use and subsequent en-route choice. After coupling en-route route choice to DRIPs as the channel for travel time information in this study it was decided to model in the ITS Modeller. Latter provides a micro simulation environment through which driver behaviour can be analyzed at the individual driver level. First opportunities for improvement in modelled driver use of information during en-route route choice were identified. The following research questions were used to further explore and implement a driver information model.

RQ1 How can the DRIP information market be characterized and how do market dynamics affect driver route choice behaviour?

Through a concise exploration the DRIP information market and visit to the Verkeerscentrale Midden-Nederland we made some interesting findings. These findings originate from the fact that the DRIP information chain is a complex system involving many technical systems but also a multitude of stakeholders. Some examples resulting from DRIP information dynamics are used to illustrate effects on route choice behaviour. The first example is formed by occasional manual operation of DRIPs by traffic controllers. During this process it appears information provisioning to drivers is prone to delays. Secondly it became clear that the small number of responsible parties for maintenance of DRIP control systems posses a large amount of knowledge seemingly necessary to maintain DRIP information quality. Both examples carry a risk of information quality deterioration and as such a the risk of losing trust of drivers in DRIP information.

RQ2 Given the lack of a driver information evaluation mechanism in the ITS Modeller: How can driver route choice behaviour be modelled and implemented?

This report identifies an apparent opportunity for improving driver route choice modelling under influence of DRIP travel time information. A driver information model is proposed in which car drivers exhibit updating behaviour on their travel time estimations and uncertainty about these times. The model fits in the current method of modelling route choice in the ITS Modeller. Our driver model is based on uncertainty about a drivers’ own mean travel time estimation and travel times provided by a DRIP. High uncertainty about his own estimation leads a car driver to update his expected travel time closer to that predicted by a DRIP. If the opposite is true then a driver updates his expected travel time closer to his initial estimation. In other words: “Updated quality perceptions are a weighted average of prior beliefs and observed quality. Weights reflect perceived reliability of prior beliefs and observations, respectively: when the traveller distrusts (trusts) his own observations, updated perceptions of quality are relatively close to initially anticipated quality (observed quality)” (Chorus & Dellaert, Forthcoming)
RQ3 What are the route choice effects of the proposed driver informing model?

The simulation phase illustrates the difference in driver travel time updating for different levels of uncertainty while all other simulation factors are kept constant. The implemented driver model indeed leads to different updated route cost under influence of travel time information. In the particular scenario comparison overall network effects due to difference in route choice behaviour were minimal though because of the small absolute difference in updated route costs. Further face validity analysis indicates that this small change in route choice behaviour early in the peak period appears to have a positive effect on travel time dispersion. This conclusion is not supported by significance and as such is made with reservation.

Based on this study we recommend the following for further research:

Practical recommendations:

- **Inclusion of truck drivers in use of the driver information model and future research.** In this study we assume the group of drivers only consist of car drivers. In practice this is not the case and this study indicated that truck drivers show different route choice behaviour in light of traffic information, specifically route and travel time information through a DRIP. The current study overestimates the effect of provided information.
- **The utility function in our study consists of travel time and travel time uncertainty.** In practice more factors may be important in a drivers’ en-route route choice consideration. Further research should investigate which factors are important.

Practical recommendations:

- **During implementation of the model it appeared that an implementation at individual driver level would lead to too high computation times.** We consider some opportunities for better implementation to be feasible. TNO has the opportunity to use server based computation. Running the improved driver information model in such an environment might result in acceptable analysis times. An other option is further evolution of the way in which the driver information model is applied to drivers. An implementation could be conducted analogous to current implementation of for example lane changing and car following models.
- **We assume the lack of influence of a DRIP on network familiarity.** In short route information of a DRIP does not lead to inclusion of a route in a drivers’ route set. Further improvement of the driver information model ought to take inclusion into account.
- **We saw that in certain situations DRIP information delays occur outside of control of the CDMS (Centraal DRIP Management Systeem).** It is deemed beneficial if the source of this delay, manual operation, is taken into consideration and how this affects DRIP information delay. Gained insights could be used to have a future calibrated driver information model more robust.
Preface

I am glad to present to you my graduation thesis which marks the end of the Master of Science program Transport, Infrastructure and Logistics at Delft University of Technology. Although the route to this capstone was a lengthy one I am glad to have taken it as it gave me the opportunity to get to know and gain knowledge in different technical and non-technical fields of research.

First I would like to thank my supervisors at TNO Martijn van Noort and Maaike Snelder for providing me the opportunity to work on my graduation assignment at TNO. At Delft University of Technology Bart van Arem and Caspar Chorus for their feedback and support during the last year. You always agreed to the many meetings which helped to direct my research. A special thanks goes to my daily supervisor Adam Pel. I very much appreciate the time and effort you invested in our discussions and feedback sessions. My desk at “het T&P afstudeershok” during the last few months at times also provided a welcome distraction from my thesis through discussions on a wide range of topics with my fellow graduates. Good luck on finishing your theses guys!

It is impossible to thank everyone, but some need to be mentioned here. Firstly my parents, mom and dad you have always done everything in your power to stimulate and encourage your children to study. Also during this last half year of studying your support was invaluable. Secondly Aartie, you must be one of the most patient people I know. Your fighting spirit during your own studies and more so during the last half year inspires me very much.

Jayant Avinash Ramautarsing
August 2011, Delft
Contents
Summary .......................................................................................................................... i
Preface ........................................................................................................................... iii
Contents .......................................................................................................................... v
1 Introduction ......................................................................................................... 8
  1.1 Problem definition ............................................................................................. 11
  1.2 Scope of research ............................................................................................. 12
  1.3 Research methodology and report structure........................................................ 14
    1.3.1 Research goals and questions ................................................................ 14
  1.4 Reading guide & report structure ....................................................................... 16
2 Traffic information ............................................................................................... 17
  2.1 What types of information are delivered through a DRIP?............................. 17
  2.2 Information during non-recurrent traffic circumstances......................... 19
  2.3 What does the Dutch DRIP traffic information market look like?............... 20
  2.4 DRIP information and market dynamics...................................................... 23
    2.4.1 DRIP information market complexity example...................................... 24
  2.5 Discussion ........................................................................................................ 24
3 Modelling driver informing through travel time information............................. 26
  3.1.1 Concise overview route choice decision theory......................................... 26
  3.2 Current modelling of information provisioning in the ITS Modeller ................ 27
  3.3 Developing/extending traveller information model........................................... 29
    3.3.1 Mathematical formulation of informing model ......................................... 31
    3.3.2 En-route expected travel time updating due to information...................... 33
    3.3.3 Modelling route choice........................................................................... 35
    3.3.4 Numeric examples of driver informing mechanism................................... 36
  3.4 Discussion ........................................................................................................ 39
  3.5 Integrating driver informing into ITS Modeller.................................................. 40
    3.5.1 Constraints concerning implementation.................................................. 40
4 Testing and simulation ......................................................................................... 41
  4.1 Testing information model................................................................................. 41
  4.2 Experimental set-up .......................................................................................... 42
    4.2.1 Determining default utility coefficient values........................................... 44
  4.3 Performing experiments...................................................................................... 47
    4.3.1 Scenario selection ...................................................................................... 47
    4.3.2 Scenarios for a confident driver................................................................. 49
    4.3.3 Simulation results...................................................................................... 50
    4.3.4 Scenarios for an insecure driver................................................................. 70
    4.3.5 Simulation results...................................................................................... 71
  4.4 Discussion on simulation results......................................................................... 88
5 Conclusions ............................................................................................................ 90
  5.1 Elaboration on selected topics.......................................................................... 91
  5.2 Recommendations for further research............................................................. 92
1 Introduction

Not too long ago, on the 28th of May 2010 to be precise, the Netherlands “celebrated” its first car traffic jam 55 years ago. That sunny Easter Sunday caused car owners, a car being quite a luxury at that time, to get in their cars and make a leisure trip (Nieuwsblad Transport 2010). The motorway junction Oudenrijn near Utrecht could not handle the flow of cars and this resulted in the first Dutch car traffic jam. Since it was the first, interested and flabbergasted onlookers decided to set up camp next to the stationary line of cars and watched in awe. Since then times have obviously changed. The majority of travellers frequently finding themselves on congested motorways would have a hard time conjuring up any positive effect from it. Many studies have been performed at trying to quantify the effects of traffic jams on society since mobility in general forms an integral part of our economies’ backbone. The European Commission estimated the cost of road congestion to be around 1.1% of EU GDP per year (European Commission 2008). In the Netherlands traveller mobility and freight transport have experienced remarkable growth over the past decades. Between 1995 and 2005 the amount of traveller kilometres has increased by 10% to 183.6 billion. Changes in socio-economic factors and an increase of the average car trip distance per traveller are at the root of this development. The bulk of the growth is caused by the use of auto mobiles, which was and still is the most popular mode of travelling. The growth in freight transport mobility with almost 25% to 120 billion tonne kilometre is explained by economic growth in general and by the increase of international trade in particular (van Mourik 2008). These growth figures combined with a disproportionate growth of road throughput capacity lead to clear increase in vehicle loss hours on Dutch roads until 2007. After 2007 the economic crisis also affected the Dutch economy and resulted in less transport movements and traffic jams. As a result vehicle loss hours also dropped. The next figure illustrates the development of vehicle loss hours over the past years.

![Figure 1.1 Dutch vehicle loss hours (in millions)](Kennisinstituut voor Mobiliteitsbeleid, 2011)

The vertical axis represents vehicle loss hours in millions, while the blue line represents actual vehicle loss hours until about 2009. The other lines are estimates of the development in the trend based on several studies in the Netherlands.

In contrast to the benefits which mobility has to society it also causes serious societal costs. Congestion was mentioned, but also noise pollution and traffic accidents place a burden on
many European citizens. Since the 2001 White Paper on transport, the Commission has intensified its gearing towards sustainable mobility. Next to pricing mechanisms the Commission also suggest supportive measures. These measures include but are not limited to intensifying the development and use of Intelligent Transport Systems (ITS) (European Commission 2008). These kinds of systems enable travellers to gather information about actual and predicted traffic conditions. The general idea behind these systems is to have travellers better informed on travelling conditions ideally resulting in well-considered decisions. Traveller decisions in turn can affect traffic system performance. The latter causes this field of research to be of relevance to road operators and policy makers. Figure 1.2 below shows a variety of ITS. Some of the systems for example aid the traveller at the operational level by detecting and warning about obstacles or inter vehicle distance, thus attempting to increase safety levels. At the tactical level drivers can be informed through dynamic route information panels or navigational systems to influence route choice. Media like television, internet and radio can be used to inform travellers on more strategic choices like activity choice, departure time or mode choice.

![Figure 1.2 Intelligent Transport Systems (source http://www.etsi.org)](http://www.etsi.org)

The contextual setting described in this chapter forms a base on which TNO develops its activities concerning the effects of ITS applications. In general these effects are classed in three groups namely those concerning traffic system flow/through put, environment and safety. This classification is shared with the Dutch Ministry of Infrastructure and Environment. The ministry has explicitly expressed this view trough the “Wegen naar de Toekomst” innovation program for example, consisting of various innovation projects. One of these projects was de Rij-Assistent during which in-car driver assistance applications were tested and evaluated (Rijkswaterstaat 2007). Since TNO have been involved with mobility, logistics and related policy topics, models have been used to support analysis and advice. With growing insight in the field of traffic engineering and human factors traffic analysis
models have undergone changes and improvements. TNOs' Smart Mobility business unit for example built a framework in which route choice could be incorporated in microscopic traffic simulation. The process by which this was done and technically implemented was documented in a user friendly way (Faber, 2007).

Travel and traffic information play an important role in traveller behaviour and traffic flows. Travellers have the possibility to use information on current and future traffic situations to make their travel decisions. Travel decisions by individual travellers subsequently influence the performance of the total traffic system. This makes behaviour of travellers an interesting topic to policy makers and road operators. In this thesis travel choice behaviour also plays a central role.

This thesis continues exploring the identified improvement possibilities. The next sections pinpoint research areas and challenges to be dealt with through the remainder of the report, and research questions are mentioned. The research problem is presented next and key areas of interest are identified. The latter will play an important role in modelling driver route choice behaviour under the influence of route information.
1.1 Problem definition

Context
As mentioned in the introduction this thesis follows a path which leads to accomplishing the goal of modelling driver traffic information use and subsequent route choice. This poses some challenges. First, a driver is influenced by his own needs, preferences and perceptions (Bovy & Stern, 1990) in route choice decisions. These factors have not been taken into account in the current way of information use in the ITS Modeller and to a certain extent will be addressed. The finding which forms the basis on which this thesis continues is that traffic information use by drivers is currently modelled in the ITS Modeller Paramics plug-in by applying a relative simple formal framework at the individual driver level at best. This deserves some clarification. The route choice model of micro simulation package Paramics is based on utility maximization with all users having full knowledge of the network and its utility components. The generation of route alternatives with changing network states due to accidents or congestion was not included. The model was extended and implemented in the ITS Modeller plug-in for Paramics by having alternative routes generated at points were network users passed traffic/travel information media. This network/link information is then used to update corresponding link travel utility measured in travel time. The latter is called disutility or cost in the remainder of this since in general travel time is experienced negatively by travellers and drivers. All route costs are recalculated and users base a new route on a c-logit model.

It is the translation of route travel times directly into route costs where questions rise. The main problem with the current mechanism is that it does not represent the cognitive, psychological and learning processes which can or do take place when a driver is confronted with traffic information. This fact leaves open possibilities for further improvement.

Secondly this thesis acknowledges the fact that driver route choice behaviour can be influenced by traffic information while the latter is influenced by dynamics in the Dutch traffic information market. Since simulation is part of this study, recommendations will be made in order to deal or take into account these dynamics. The next section continues a bit more on information market complexity.

Market complexity
Market dynamics are caused by a multitude of factors. Parties like national or regional authorities changing their views on traffic management form an example. When mentioning governmental policy this is subject to change under influence of recurrent elections, roughly every four years for the Netherlands. Apart from these public parties, private parties also play an important role. Companies like TomTom, Garmin, Mio, VDO Dayton, HP, Asus, Harman and many more have stakes in personal navigation systems. These companies develop and sell their own traffic information systems. Currently the bulk of these systems still provide static route information but it is projected that dynamic traffic information will be provided on a large scale to travellers in the near future. These systems can be seen as competitive to traffic management by public parties. Information from both provided at the same time might contradict each other causing confusion with the traveller. Private systems not only compete with public services, they also often use other types of source data which is used to generate traffic information. This results in service providers being in control of an entire traffic data logistics chain from raw data gathering to information provisioning to the customer.

Information market complexity can have an impact on information quality, the way by which this happens in the case of a DRIP for example as a means of traffic management has to be identified to some extent. Possible consequences for an implemented driver information learning model can then be qualitatively estimated.
1.2 Scope of research

Content related
In general route choice by drivers is governed by two main factors (Bovy & Stern, 1990):
- The traveller, with his subjective needs, experiences, preferences, perceptions, etc.;
- The physical environment, with its objective opportunities and their characteristics.
The last factor for example includes the road network, routes between origins and destinations, traffic management instruments and so forth. The route choice process and its context can be illustrated as in figure 1.3 below.

Figure 1.3 Context of driver route choice process, adapted picture (Bovy & Stern, 1990)

The figure indicates that traveller and transport network characteristics involved influence route choice behaviour. Transport network characteristics in this sense pertains to many factors not only limited to the built environment but also including perception of network elements such as traffic management measures and travel and traffic information.

En-route & DRIP
Focus of this thesis is put on en-route route decisions by drivers. In the Netherlands drivers can be informed about routes through several channels which include radio, navigational devices, internet and DRIPs. Taking into consideration the aim to focus on en-route route choice, DRIPs are the dissemination channel since other channels also affect pre trip route choice. It is possible however that DRIPs also affect pre trip route choice, a driver might prefer a route over another as he knows there is a chance of receiving information while en-route. During this study however this possible pre-trip route choice effect of a DRIP is not taken into consideration.

Compliance rate
Furthermore in the TNOs’ ITS Modeller a compliance rate determines the share of drivers which actually sees DRIP information in the first place. It is expected that an increase in the compliance rate of the DRIP also results in a positive linear increase in rerouting driver percentages. This study does not investigate the compliance rate of a DRIP. Throughout all analyses it is kept at the default value of 1.0 meaning all drivers passing the DRIP and receiving information about their planned route decide whether or not to reroute. In reality this is not the case as not every driver actually notices or wants to use DRIP information.

DRIP information end use
In this study car drivers are the end users of traffic information. They can use provided route information during their (en) route choice decisions.
Scoping on route choice behaviour by car drivers means truck drivers are not part of this study. The scientific body of research on differences between route choice behaviour truck drivers and car drivers is limited. However in practise route choice by truck drivers is governed largely by employer routing schedules and in cases for which truckers would have a choice to deviate from planned routes they are hampered by their vehicle size (Ministerie van Verkeer en Waterstaat, 2004b) and infrastructural characteristics like overpass clearance and road with. These important elements of route information to truckers are not (yet) included in either DRIP or widely available commercial navigation devices without investing in more professional solutions like TomTom WORK. In general attitude towards DRIP information and route choice behaviour of car drivers and truckers is quite different (Peeta et al., 2000a).

This to some extent has implications for simulation results later in this report, namely a probable overestimation of route choice effects due to provisioning of route travel time information.

This study also does not cover driver choices on activity, destination, mode and departure time. It can be argued if this is a justified decision at the start of this project, however previous studies and literature reviews (de Goede et al., 2010) believe traffic and travel information affect route and travel time choice the most. Furthermore, this scoping decision is justified by European and Dutch traffic and travel management policy shifting focus to usage of existing infrastructure instead of realising large scale modal split effects (European Commission, 2001). Further

**Motivation**

This report is written as part of an graduation assignment at TNO and provides the possibility to gain some experience in the field of traffic management research while at the same time finishing the graduate course. During the Transport, Infrastructure & Logistics masters course a broad view was kept while taking part and successfully finishing courses from a wide range of disciplines. The introduction of this thesis illustrated what the negative effects of road congestion are. The outcomes of this research could potentially be applied to future DRIP evaluation studies by TNO and as such has a sound societal relevance.

**Scientific relevance**

The scientific added value of this graduation assignment is not so much aimed at developing new traveller behavioural models. It aims however to identify areas of interest within the traffic simulation tools used at TNO and through further focussing on these areas identify and improve traveller behaviour under influence of traffic information. Suggested improvements are executed by applying a driver information informing model and performing simulation experiments.

**Practical relevance**

This research aims to successfully implement a theoretical driver behaviour model in a practical operational research setting. It enables TNO to gain insight into this previously unimplemented driver informing model.
1.3 Research methodology and report structure

In order to tackle the issues mentioned in the problem definition we determine some research questions (RQ). These questions are answered throughout the rest of this thesis.

1.3.1 Research goals and questions

The objective of this research is to implement a model which represents a driver informing process under the influence of travel time information. The way in which this process is modelled and implemented needs to be addressed, as well as the effects on driver route choice. In order to achieve the formulated objective research questions are identified. These questions find their origins in the areas of interest introduced in chapter 1 and have a direct link to the stated research objective.

RQ1 How can the DRIP information market be characterized and how do market dynamics affect driver route choice behaviour?

- What type of information is provided by DRIPs?
- Which parameters concerning individual traveller behaviour change during incidents?
- Can market developments affect the fundamentals of the behavioural framework?

Data need: Status of the DRIP traffic information market and current modelling method of traffic information use in driver route choice decision in the ITS Modeller.

Data source: Literature (scientific papers, in house TNO research and documentation), experts

Method: Desk research on the mentioned scientific fields, expert opinion.

This question is answered in chapter 2. It provides an introduction into the DRIP information market. A choice for a driver informing model then raises the following question:

RQ2 Given the lack of a driver informing mechanism in the ITS Modeller: How can driver route choice behaviour be modelled and implemented?

- Provide a concise overview of theories which have received considerable attention in the field of driver (route choice) behaviour.
- Which model is implemented in the ITS Modeller at TNO?
- What are the underlying behavioural assumptions?
- How do these model assumptions relate to route choice behaviour in reality?

Data need: Status of knowledge in the fields of decision theory and traffic engineering.

Data source: Literature, experts.

Method: Desk research on the mentioned scientific fields, expert opinion.

This question is answered in chapter 3 and leads to an implementation of a driver informing model in the same chapter. While dealing with these questions and taking into account the context in which the informing model is placed the following question arises:
RQ3 *What are the route choice effects of the proposed driver informing model?*

- Does the model also maintain flexibility to adapt to specific non-recurring traffic situations like incidents?

**Data need:** Real data from scenario analysed with model. This data is used to validate the model. At this point and with respect to the topic extensive data sets are hard to find. In case no data is available validation will have to be done by use of estimated parameters.

**Data source:** Measurement data sets or estimation in case of a hypothetical approach.

**Method:** Performing simulation experiments with the proposed model to assess and illustrate the effect of the implemented behavioural model.

In chapter 4 we use the implemented model to conduct experiments in the form of scenarios. The effect of information on drivers is assessed by using network performance indicators. These include indicators like average travel times, mean speeds and route choice statistics.
1.4 Reading guide & report structure

Chapter 2 continues with an introduction into the Dutch traffic information market and its dynamics mainly concerning DRIPs. The third chapter continues on driver route choice behaviour and proposes a driver information information model. The model is then implemented which is qualitatively described in the same chapter. The fourth chapter consist of conducting experiments with the ITS Modeller and driver information model and presenting model output and insights. The thesis is finalized with chapter 5 providing conclusions and recommendations.

The following chapter continues with DRIP information and the DRIP information market.
2 Traffic information

This chapter partly answers research question

*RQ1 How can the DRIP information market be characterized and how can market dynamics affect driver route choice behaviour?*

As mentioned in the scoping part of this thesis, DRIPs are taken as the means to disseminate traffic information to drivers. The chapter will start with these message panels and the information they present to drivers. To complete the picture it is positioned in the Dutch traffic information market with its complexity and dynamics. As such this chapter provides background information and the context of driver route choice behaviour and informing under influence of DRIP travel time information.

2.1 What types of information are delivered through a DRIP?

Background information for this part was partially available within the TNO organisation, namely its Human Factors division in Soesterberg. A literature search in their database revealed interesting research data. Focus of data collection was often put more on operational driving tasks instead of route choice. Some of the research projects however also included effects of information provisioning through DRIPs on route choice.

In the Netherlands a few types of DRIPs are in use. The first type was introduced roughly 20 years ago and is still the most used type. In general they have evolved to display text on three lines. The text messages can contain a combination of a congestion warning, its location, source of congestion and effects on travel times or queue lengths. Also road section closure and advised rerouting can be displayed. Some of its earliest implementations were on the north section of primary road network surrounding the city of Amsterdam. A picture of this early type of DRIP along side a recent model is provided in figure 2.1 below.

![Figure 2.1 Early type DRIP on the left, recent model on the right](image)

The second type is information panels with extended functionality in the ability to provide graphical information. These panels are called GRIPs (graphical route information panels). In the Netherlands its use is being intensified. A picture of this type of panel is provided below.
This type of sign is capable of presenting a graphical overview of a section of network. Additionally it can dynamically display queues on affected network segments. This particular example however indicates the presence of a queue in red but does not indicate its length or expected travel time.

Both types of panels are a means to disseminate traffic information to drivers being part of the last step in the process of informing drivers through a local public channel. Route information on these panels is presented in different ways. The nature of messages can be described as (Janssen et al, 1992)

**Prescriptive route information**
A traveller is provided a recommended route choice without actually mentioning any information on traffic/route characteristics for any of the alternatives. A road operator tries to achieve some traffic management goal by providing this type of information. As mentioned earlier these goals can for example consist of better traffic flow or to maintain safety levels.

**Descriptive route information**
This type of information includes a status update on traffic/route characteristics. It is the opposite of the previous class as no route choice advice is given and travellers can use it to make their own route decision.

**Combination of both**
Information of this type combines both previous classes, coupling traffic/route status with route advice.
A fourth category also exists however does not concern route information. Since a number of years the ability exists to mention slogans on the panels. These range from reminding seat belt usage to mentioning the Dutch DoT website.

In the Netherlands extensive guidelines have been determined by which the text on DRIPs is controlled. These guidelines are used by national and regional road operators as well as regional traffic centre operators to harmonize DRIP control in case of: dynamic traffic information, road works, incidents, leisure events, regional or national slogans and explanatory purposes during activation of dynamic traffic management measures which drivers are confronted with (Rijkswaterstaat DVS, 2010).
2.2 Information during non-recurrent traffic circumstances

During this project the interest in information provisioning during incidents was also fuelled. Partly this was due to the authors’ previous involvement in a research project involving information provisioning in disaster situations, although not traffic related. On the other hand some interesting insights were gained during for example a visit to the Dutch Regionale Verkeerscentrale Midden-Nederland, which is the traffic centre responsible for monitoring safety and traffic throughput on highways for the centre region of the Netherlands. Intuitively information provided through a DRIP becomes more useful to a driver in case the driving conditions he faces become less familiar and more unpredictable (Chatterjee and Mcdonald, 2004). Such conditions can be an accident, road maintenance or a major sporting event attracting a lot of visitors. It is in these circumstances that providing travel or delay times supported by mentioning its cause (Bonsall, 1992) potentially have the biggest impact on information credibility and ultimately route choice.

During his research in road incidents and network dynamics effects on driving behaviour and traffic congestion, Knoop (2009) also analysed data from five road incidents. These incidents differed in severity and effect on road capacity. He found that with more severe incidents, including blockage of the majority of lanes on a high way, route diversions were relatively high. At the same time he found that the reaction of drivers to the incident situation showed a delay. A cause for this delay might lie in delayed route information which becomes available to drivers. At the level of individual modelling of driver behaviour in microscopic simulation, several behavioural parameters change during incident situations. Knoop firstly found that drivers choose a different head way at bottlenecks caused by an incident than they do at normal bottlenecks. The mean of driver head way is higher at incident sites. Secondly he found that reaction times of drivers at incident locations are much higher than under normal situations. These insights indicate the need for adaption of these parameters in a microscopic model. In case of the ITS Modeller these parameters can be altered in specific Java classes describing different driver tasks. During the simulation experiments described in chapter 4 these parameters were not changed, actually apart from the proposed informing model and immediate related model components no other driver tasks and processes were incorporated in this study. This is a limitation and as such should be addresses in future route choice studies involving the information model during incidents. For this study it means that an incident merely functions as a traffic event which causes the blockage of a lane and thus contributes to the build up of (additional) congestion.

At the individual driver level research also indicates that situations in which travel time delays are unwanted, drivers are least prone to follow the behaviour of other road users (Janssen et al, 1992). At the same drivers who are susceptible to rerouting advice show the tendency to adapt their driving style earlier then drivers who are less susceptible. This results in early adaption of driving speed and changing lanes in order to follow rerouting advise (Janssen et al, 1992). Other factors also may play a role in a drivers’ reaction to route information on a DRIP, for instance intoxication and age. Age has a positive correlation with reaction times to information on a DRIP, especially at weaving lanes (Janssen & Martens, 1997).

During a visit at the previously mentioned traffic centre, topic of conversation (see Annex 1 for a summary) also included DRIP operation and route information during incidents. It turned out that the decision to display the incident event, travel/delay time and rerouting advice on a DRIP was incidentally not done through the CDMS\(^1\), but manually. The process

\(^1\) CDMS = Centraal DRIP Management Systeem (Central DRIP Management System)
of deciding to advise on rerouting and manually activate the text on a DRIP included the use of at least two computing/decisional tools. At the same the observer has to deal with the incident itself including closing lanes, coordinating with emergency services and ordering for a tow service or salvaging crew. Intuitively priority is given to the latter activities in order to restore safety at the incident location. This insight is important in considering traffic information provisioning through DRIPs during incidents.

2.3 **What does the Dutch DRIP traffic information market look like?**

The Dutch traffic information chain can be described through a few main elements and processes. These can be summarized by measurement, collection & processing, dissemination and end use as illustrated in the picture below.

![Information chain](image)

**Figure 2.3 Information chain, adapted picture from Koopmans (2007)**

For this study the following description for the different steps can be given.

**Measurement** In this phase raw traffic data in both chains is gathered which is used to provide traffic information. Up to and including 2014 traffic data will substantially be gathered by detection loops and video camera monitoring assisted by automatic number plate recognition (KiM, 2011). Detection loop technology can be considered to be amongst the oldest of traffic surveillance systems. Loops only provide data for those particular sections of road where on actually has been placed underneath the road surface. Next to being a fairly area restricted technology, set up and running costs are relatively high. This is why video technology in combination with (number plate) recognition has been in use for a number of years now. These systems not only have a much larger detection area compared to loop technology, they also are capable of streaming useful visual data to the Dutch
regional traffic centres adding extra value to functionality. Aided by the visual data traffic centre operators are able to quickly detect road incidents and act accordingly. Private actors which are also active on the traffic information market use different sources to gather traffic data. The first attempts to use mobile phones as probes for traffic analysis were during the Cellular Applied to ITS Tracking and Location (CAPITAL) program. The system however turned out to be inaccurate in its estimations. In Europe the STRIP project (Valerio et al. 2009) in France initially showed promising results, however speed estimates on certain urban ring segments also lacked accuracy due to frequent stops. More recently Vodafone and TomTom have joined commercial forces with Vodafone providing cellular data to TomTom for its dynamic route information services. Floating car data (FCD) essentially are continuous speed measurements at individual car level while these move through traffic. With modern electronic car management systems many more parameters than speed alone can be monitored (Huber et al., 1999). These parameters also include environmental information on external temperature, rain sensor data and air-conditioning. Next to this also information from driver assistance systems, warning and brake light operation can be monitored. The extension of FCD with these parameters is called extended floating car data (EFCD/XFCD).

In terms of analysis of route choice behaviour these methods of traffic measurement have a varying level of explanatory value for analysing and describing individual route choice behaviour. DRIPs on their own for example, which are used in this report during simulation, provide network performance data on an aggregate level. Difficulty arises in interpreting data when multiple weaving areas exist on a stretch of road network. Merging and separation of different traffic flows then cause distortion in route choice analyses, especially at the individual driver level. As said earlier in this section a combination of loop detector data and cameras provides a possibility to overcome this problem. The use of data on an individual driver level which is done by TomTom for example provides an alternative source of route choice data. It remains questionable however to what extent public information disseminated through a DRIP for example will benefit from such a source. It would involve sharing of private commercial data which is highly unlikely to happen in the near future, at least on a large scale.

Collection & Processing In this phase raw traffic data is collected, stored and if needed adapted in order to be used for traffic state analysis and determination of relevant traffic state information. In the Netherlands the flow of traffic data from loop detectors can be illustrated through the following overview. It must be noted that the overview depicts the system which is used for public information provisioning and road safety surveillance by public operators.
While this research does not analyse the various subsystems in great detail some clarification is needed. In the left corner the road side systems are mentioned which provide the data feed for the rest of the information chain. These systems, loop detectors and video registration, were mentioned previously under “Measurement”. At the centre of the system is MoniCa which receives input from both MTM2 and the road side systems (Adviesdienst Verkeer & Vervoer, 2006). MoniCa verifies, validates and adapts the data it receives from the two data sources. The adapting process includes for example aggregating the data on a bigger time line and calculating total and average section speeds. At a minimum interval of 1 minute network state indicators become available for a range of applications. One of these is the CDMS which is used by the Dutch traffic management centres to control text strategies on the DRIPs. The manipulation of the text strategy is operated automatically by CDMS or can be overridden by traffic centre operators in case of emergency.

With regard to the flow of information from public to private data collection and processing as presented in figure 2.3 the following can be said: The NDW (National Data Warehouse) has been operational since 2009. At the end of 2010 data from 3000 kilometres of road network data was available through the warehouse. During 2011 the database is planned to be extended to 5000 kilometres including high ways, regional motor ways and urban arterials. This institute functions as a data broker for both public and private market actors. Simply stated, through the NDW private service providers now have access to a second stream of traffic data next to their own sources. In return for a set annual fee this data is made available and can be used by private service providers to maintain or increase their own traffic information quality. Some Dutch examples of private parties which use NDW data are Fileindex.nl, Onderweg.nl and KPN for its OpWeg navigation service (NDW, 2011). With the extended network database still an important part of possible alternative routes are not incorporated, namely those routes which use secondary roads. This remains a downside to such a database as private parties also have databases containing traffic measurements at secondary network levels. Subsequently route information through DRIPs has to be manually supplemented by traffic centre operators in certain traffic situations. Route information then becomes in part dependent on human monitoring for example by mobile road inspectors and emergency services, increasing the risk of information quality degradation. At the same time
parties can opt to use NDW data if they provide their own processed data to the NDW. It appears that private companies with a traffic data base of their own currently do not use this option, claiming their data bases to be more complete and having higher information quality. This is illustrated by the dashed arrow in figure 2.3.

**Dissemination** In general public route information is provided through a range of channels which are used by public parties for traffic management purposes. These channels include for example traffic signalling (traffic jam warning), speed limit measures, junction merging and dynamic route information panels. From a private commercial view point travel and traffic information is also provided through different means which include dynamic navigation systems, parking reference systems and systems that generate (multi-) modal travel information (van Arem et al., 2008).

**End use** In this study car drivers are the end users of traffic information. They can use provided route information during their (en) route choice decisions.

### 2.4 DRIP information and market dynamics

How does information quality affect a driver? Intuitively quality of provided traffic information has an influence on whether or not a driver notices, accepts and takes it into consideration in the route choice decision making process. This at least would be the case for a driver looking for or susceptible to traffic information. One can imagine that the importance of traffic information and route guidance plays a different role for different types of travellers. Commuters for example often travel on a limited time budget and are particularly interested in reaching their destination on time. Recreational travellers on the other hand tend to travel less by a time budget are more keen on taking the right route since they are often geographically unfamiliar.

In general traffic information and service quality become more important to travellers as they get increasingly experienced with its use (Lappin, 2000). The effect and success of information systems has also been studied in other fields of research. Over the past decades the success of information systems was extensively researched by McLean & Delone (1992, 2007). More recently information system success was also increasingly studied in the field of disaster management by Bharosa (2011). Although the contexts are different it appears that information and system success, also in traffic information application, is dependent on some fundamental factors. These factors include reliability, relevance, accuracy, timeliness, cost, degree of decision guidance and personalization, convenience (ease of access and speed) and safety of operation (Lappin, 2000). Information quality is further included in the next chapter in which the proposed model for driver behaviour based on travel time and travel time uncertainty is introduced. Reliability in terms of driver perception and expectation of uncertainty in travel time estimation plays an important role in the model.

In the case of the Dutch DRIPs quality of information provided to drivers depends on the underlying measurement and technical systems involved. Figure 2.4 in the previous section of this chapter and the accompanying elaboration indicated which subsystems are involved in DRIP information provisioning. In essence traffic information markets show a tendency to produce clusters of market actors which cooperate in the dissemination of traffic information to end users. The first part of this chapter already gave some examples of this clustering. One mentioned was cooperation between Vodafone and TomTom, with the latter combining its own traffic data gathered from navigation devices with mobile phone movement data from the telecom provider. A second example is the clustering of parties in case of DRIPs. This information service is provided according to public goals and interests like road network throughput and safety. The fact that the DRIP system is a public responsibility combined
with the financial magnitude of for example maintenance on its control system CDMS results in mandatory periodical tendering. This results in added complexity and dynamics to the Dutch traffic information market. We do not provide an analysis of the Dutch tendering process but give the example from a judicial viewpoint in order to illustrate how this complexity and dynamics could influence quality of traffic information.

2.4.1 DRIP information market complexity example
In the Netherlands Vialis, a subsidiary of Volker Wessels, is responsible for maintenance of the CDMS. In 2006 the maintenance contract which included amongst other traffic management measures the DRIPs and its controlling system CDMS had to be renewed. This was done through a public tender according to legislation in light of the financial and societal impact of the project. The tendering process which followed resulting in the original developer Vialis winning the tender was not a straight forward one. The outcome actually had to be decided in court after other bidders had demanded the exclusion of Vialis from the tendering process because of a claimed unfair advantage on the side of Vialis. Having built the control system in the first place and having an extensive database on past and current system bottlenecks/errors supposedly provided them with more expertise and knowledge on essential system information and history then the other parties (2007). Ultimately Vialis did win the tender, but this short elaboration illustrates not only the technical complexity of the topic, but also the organisational and judicial issues and market complexity surrounding a traffic information system including the DRIP as means for dissemination.

One can wonder what would have happened if Vialis had not won the tender and the CDMS had to be serviced by another company. Vialis was highly reluctant to share information about this system with other private competitors, using the argument that since they had developed and built the system this would have resulted in a breach of their intellectual property. Such a stance of Vialis would increase the risk of information quality deterioration due to less or inappropriate system maintenance on the long run. The possible information quality drop could then negatively affect its end user (driver) valuation and ultimately use in route choice consideration.

2.5 Discussion
A car driver is usually only confronted by the dissemination means of this chain, whether it is a DRIP, an internet service provider or a personal navigation device. The introduction into the traffic information chain and driver route choice behaviour so far has shown that it is complex from different perspectives. From a technical point of view a lot of systems are involved in getting traffic information to the end user. We illustrated that information is displayed using different text strategies and that the success of information provisioning in terms of effect on route choice behaviour depends on traffic circumstances and individual driver characteristics. This study makes assumptions on both and this results in the need for researchers to acknowledge that these parameters in practice do have an influence on driver (route choice) behaviour. It was mentioned for example that intoxication and age are related to driver reaction to DRIPs.

The operation of DRIPs during non recurrent situations like incidents was shown to be occasionally done by traffic centre operators. In these situations operation is often conducted manually which carries a high risk of retarding information provisioning via DRIPs during incidents. Considering that drivers in practise do learn from experiences facing the lack of information during these circumstances might affect driver trust in this information channel in general on the long run. In relation to the driver informing model this would result
increasing the level of uncertainty of information thus leading to drivers having an updated travel time close to their own initial expectation. Not only technical and operational factors cause complexity, the development of traffic management policy and the presence of different actors also cause complexity and dynamics in the DRIP information chain. This was illustrated by adapting a judicial view and considering the issues which arose during the 2006 tendering procedure for maintenance of the CDMS. The consequences of the outcome of this process could have resulting in short term degradation of information quality due to inappropriate maintenance. As the driver informing model assumes a ratio for the utility coefficients and level of driver uncertainty about travel time information this market development would have a direct effect on these parameters.

The answer to question
*RQ1 How can the DRIP information market be characterized and how can market dynamics affect driver route choice behaviour?

is that information provisioning and driver route choice behaviour is part of a complex arena. Complexity is not only created by a multitude of systems between which DRIPs as a media for travel time dissemination functions, but is also caused by the involvement of many different parties. In the DRIP information chain these systems and parties have different influences and play different roles in driver route choice behaviour. A few examples were put forward which could affect driver route choice behaviour under influence of DRIP information. We see that during incident situations DRIPs are on occasion operated manually by traffic centre operators while they focus attention at the cause of an incident. In these situations operation is conducted manually which carries a high risk of retarding information provisioning via DRIPs during incidents. Considering that drivers in practise do learn from experiences facing the lack of information during these circumstances might affect driver trust in this information channel in general on the long run. Although just a few parties are involved with maintenance of the DRIP control systems, these parties possess essential knowledge on maintenance regimes and DRIP and system defect history. Their reluctance to share this information with others can possibly negatively affect DRIP functioning as illustrated through a judicial view considering the issues which arose during the 2006 tendering procedure for maintenance of the CDMS. The effects on DRIP functionality then result from incorrect maintenance or lack of oversight on error history of the CDMS by a third party. Again this in turn can affect driver trust in the DRIP system causing DRIP information to have less effect on route choice behaviour.
3 Modelling driver informing through travel time information

Based on scope choices until now this chapter continues with the effect of traffic information on route choice behaviour by car drivers. A concise overview of existing driver/traveller behavioural theory is provided after which the link is made with traffic simulation of route choice at TNO. From theory an information learning approach is selected and further elaborated on, leading to a proposed implementation in the ITS Modeller and answer to research question:

*RQ2 Given the lack of a formal driver informing mechanism in the ITS Modeller: How can driver route choice behaviour be modelled and implemented?*

3.1.1 Concise overview route choice decision theory

Individual driver decision making plays an important role in this research. This is illustrated by the fact that decisions made by individual drivers not only affect their own travelling experience like but not limited to perceived comfort levels, travel distance, total travel time and trip delay time. Decisions made before and after departure also affect the same parameters for all other drivers on the same network. When for example driver A chooses to take route x to his destination, he might run into a traffic jam on route x and have no other option than to join the queue of waiting cars. At the same time driver B might be driving on the same route and also encounters the same traffic jam. The fact that driver A chose route x has now caused driver B to experience a higher level of perceived discomfort and a higher amount of delay time than if driver B had taken another route. This might seem trivial but it illustrates how individual decision making not only affects the decision maker. On the contrary, the actions of individual drivers also affect the perceived discomfort levels of fellow drivers on a given network segment.

Random utility modelling is a widely used approach in modelling discrete (route) choice behaviour. Random utility theory in essence is built on a number of assumptions. The first is that route choice is considered a discrete event. In terms of driver behaviour and route choice this means route choice is a choice process while route alternatives are part of a finite discrete route set. The second assumption is that the utility of choice alternatives varies across individual drivers as a random variable. The random variable is included since the underlying factors determining this variation in utility across drivers are not observed by the researcher. The third assumption is that each driver is considered to be a rational economic being applying a utility maximizing strategy. The latter implies with regard to route choice that a driver chooses a route by a trade off between all routes available and has knowledge about their cost in term of travel time, monetary cost and other relevant characteristics. The resulting choice of a driver will be for that alternative which is perceived as most beneficial or alternatively as least costly.

As driver decisions are often made in some state of uncertainty consider a driver who uses a certain part of road network for the first time during a commuting trip. Given the fact that it is the first time driving in the area, the inexperienced driver considers a choice between route alternatives a risky undertaking. In light of this uncertainty the resulting route choice by this driver is determined by considering the expected utilities of his route alternatives. This approach is an extension of utility theory in that uncertainty of travel alternatives is taken into consideration. Expected utility theory in turn is also compatible with discrete (route) choice models resulting in random expected utility models. The latter approach is applied in the remainder of this chapter with the proposal of the driver information evaluation model. This approach is applied as it is compatible with the current method of discrete route choice modelling in the ITS Modeller.
Besides the expected utility based approaches also a considerable amount of others exist. The way for which was probably paved by Tversky and Kahneman (1979) who developed and introduced the Prospect theory. It provides a more behaviourally driven alternative to expected utility theory, with one of the main differences being the basis of weighing gains and losses of alternatives to a current situation instead of final utility of alternatives. Also many non utility based theories have been developed and have been applied to traffic and route choice behaviour modelling. The remainder of this report follows an expected utility based approach. The main reason for this decision was the ability of incorporating an informing model of a driver including travel time and uncertainty in one model and compatibility with the existing route choice model.

3.2 Current modelling of information provisioning in the ITS Modeller

Traffic information processing by car drivers is currently modelled by the use of relative linear relationship at the individual driver level at best. This deserves some clarification. Previous research has developed and implemented a more advanced route choice model than was originally available. The initial route choice model was based on utility maximization with all users having full knowledge of the network and its cost components. The generation of route alternatives with changing network states due to accidents or congestion was not included. The model was extended and improved by having alternative routes generated at points where network users passed traffic/travel information media. This network/link information is then used to update corresponding link travel costs measured in travel time. All route costs are recalculated and users base a new route on a C-logit utility function. It is at the point when route information on travel times is directly translated into route costs where questions rise. The main problem with this process is that it does not represent the psychological processes and learning effects which were mentioned earlier in chapter one. This fact leaves open possibilities for further research.

With this short introduction of route choice model a more detailed description is needed since this research is aimed at continuing development on the driver behaviour model(s) ultimately used in the ITS Modeller to predict route choice. The route choice model was introduced to enable simulating the effects of traffic information on the traffic flows on network level. A route switching approach was used to model on-trip route choice behaviour based on traffic information. The developed route choice model is a discrete choice model in which individual drivers select a route from a set of alternative routes. The route choice model consists of the following steps: Route set generation, pre-trip route assignment, updating of route sets based on traffic information and on-trip route assignment. Information in this section is partly found through ITS Modeller documentation (Faber, 2007) and referring to implemented code in the ITS Modeller java environment.

**Route set generation.** A set of reasonable routes is generated between each origin and destination. It uses a shortest path algorithm to calculate a shortest path based on the link cost utility value. In the basic implementation the link cost utility value is only a function of the travel time.

The route sets are generated in a separate simulation run. Route sets are generated using a Monte Carlo method. By running the simulation the link travel times change. With every five minute time step generalized route costs change. Every five minutes a new shortest path is calculated. A different shortest path form the previously found shortest path is included during the generation process. The total route set which is created at the end of this so called pre-run is used by drivers during following experiment runs.
**Pre-trip route assignment.** The route selection algorithm selects a route from the route set of the corresponding origin destination pair for each vehicle. A C-logit algorithm is used. This algorithm uses a random factor to create a distribution of vehicles over the alternative routes. The lower the route costs are the more drivers it attracts. The added value of the C-logit model as opposed to a standard multi nominal logit model is that it takes into account overlap in routes. In short this means that route alternatives sharing a considerable part of the route do not receive the same traffic loads as a fully non overlapping route. The total utility of overlapping routes is penalized in order to compensate for this overlap. What would be against using the normal multi nominal logit approach? The main issue with this is that equal link/route traffic loading tends to exceed route capacity for those links which overlap, leading to traffic queuing.

**Update route set based on traffic information.** The influence of traffic is modelled through traffic information messages. A traffic information message is defined as a list of characteristics of traffic information. These characteristics that define the traffic information message are the type of traffic condition (e.g. ‘congestion’), the sending time, the location in terms of links (e.g. links a, b, c and d) and the size of the congestion on every link. This abstract way of modelling traffic information systems enables modelling different traffic information systems.

The traffic information influences the links cost utility value. The link costs value of ‘Congested’ links for instance, is adapted to a delayed link travel time based on the link in question. The utility costs of all routes that contain any of these links for which information is available are updated. This results in updated route sets. These updated route sets may result in a different distribution of the vehicles over the routes, as the route choice model is run again after an information update.

**On-trip route assignment.** When traffic information about the current route of the vehicles in the network becomes available, drivers may reconsider their routes. From the route set a vehicle selects a subset of routes that are still accessible to him. In pre-trip route choice decisions all vehicles between an origin and a destination choose their route at the same place and can therefore use the same route set. With on-trip route switching decisions, drivers are all at different places in the network and all make different decisions. This requires changes to the pre-trip route sets in order to use them for on-trip decisions.

![Figure 3.1 Entire route set (left picture), route sub set for vehicle (right picture)](image)

The first difference with pre-trip route selection is that not all routes may be accessible for all vehicles. As shown in figure 3.1 above, vehicles leaving the origin have three alternative routes in their route choice decision. The vehicle in the right overview can only choose two routes because it already passed the intersection where route 1 diverts from the other routes.

A second difference from the pre-trip route selection is that relative route cost utility values change with the position of the vehicle. The position of vehicle on the road segment does matter for the relative overlap of the routes. The vehicle is at a link where the routes overlap. If it proceeds the remaining parts of the routes 2 and 3 overlap relatively less. The correction for the overlap of the C-logit model is therefore different for each location of the vehicle if the route switching model decision is modelled as a new route choice decision from the current location to the destination.
Given the insights gained thus far, the next section proposes a method for dealing with the apparent lack of driver evaluation of route travel time information. The proposed method was chosen mainly since it fits within the current c-logit route choice model which is deemed appropriate for further simulation analyses. The next section continues with the description of the driver informing model, its mechanism and assumptions.

### 3.3 Developing/Extending Traveller Information Model

This section provides a description of the proposed and designed model for driver route choice behaviour. To be more precise it provides a description of a model in which travel experiences of car drivers are incorporated in a learning process. The driver information process includes the updating of driver travel time expectation with provided route travel times through traffic information. The model only incorporates en-route route choice behaviour caused by new route travel time insight provided by a DRIP. In the remainder of this document we consider the case in which traffic information is disseminated through a dynamic route information panel (DRIP).

In addition to this introduction a few general model and design assumptions (coded by Ay below) are stated. These assumptions are made both on research scope and modelling technique:

**A1.** [Travel behaviour; route choice] In addition to the absence of pre trip behaviour changes mentioned earlier with DRIPs, no pre trip changes in travel behaviour are to be analysed in general. According to the general accepted stages of travel and transport decision making, this means mode and departure time choice are not considered but route choice is.

In addition a change in the model utility structure does not lead to a change in traffic demand.

**[Implication of A1]** In reality a part of the total traffic demand might increase, decrease or shift due to changing utility structures. This effect is not incorporated in the model and demand is represented by inelastic OD-matrices. The use of a departure time profile introduces traffic demand development during for example the morning rush hours. This is an assumption on research scope. Over the past years road pricing has been a hot topic in the Dutch traffic engineering field. With the political developments in 2010 existing large scale plans for road pricing have been put on an indefinite hold. Future framework extensions should include the effects of traffic management measures as road pricing.

The assumption of information having only an effect on route choice is a clear limitation on the research scope. With respect to traveller behaviour in practise it is a quite limiting one. More so considering the potential effects of advanced forms of traffic information systems like dynamic route advice and other sources of information providing real time traffic information. In this particular study however, since information dissemination is performed through DRIPs the effects on trip destination, mode and departure time choice are not incorporated.

**A2.** [DRIP; network knowledge] A DRIP only has an effect on travellers familiar with routes mentioned on a DRIP. In other words, route information provided by a DRIP does not result in the addition of an alternative to ones route set if a particular route was not present prior to reaching the DRIP. In short there is no effect of a DRIP on network familiarity.
**Implication of A2** From a traffic engineering point of view this assumption can be supported by studies postulating that these kind of message signs solely have an effect on already known route alternatives. One can question how the model would deal with an incident situation in which a certain route is totally blocked and diversion is necessary. In case of total blockage a route ought to be added to a driver’s route set in order to at least provide an opportunity to divert. As such this assumption effects modelling and is not a strong one.

**A3. Driver informing mechanism** In the context of this research the proposed driver informing effects are only based on expected travel times, travel time information and involved uncertainty on part of the driver.

**Implication of A3** In practice drivers would also have dynamics in their perception of for example an information channel. A driver might start very trusting on a DRIP, but after passing one a few times and discovering a noticeable difference in his experienced travel time, his initial attitude might change. The assumption that the informing mechanism only effects route preference is a strong one in this study and resulting analyses outcomes should be interpreted with this fact in mind.

This analysis aims to better predict the effect of ITS applications on traveller route choice by including driver informing through traffic information. Practically this means that the current way of estimating the effect of traffic information at TNO does not contain a form of information learning. In order to do so the introduction of a driver informing mechanism has to be placed in the general structure of current route choice modelling. Route choice as modelled at TNO by the micro simulation tool ITS Modeller currently can be described with the following general route choice visualization. The dashed arrows and boxes in figure 3.2 on the next page indicate that the provisioning of traffic information depends on traffic condition. Practically this implies that route information provisioning is active when current traffic conditions worsen due to a full link blockage or severe congestion. This part of the model is also active when traffic conditions get better. The boxes on the outer edge of the figure indicate the method of modelling in the ITS Modeller. The inclusion of the proposed information learning behaviour leads to a simplified visualisation provided in the following figure 3.2. It contains the ITS modeller components which have been mentioned until now.
The routes.txt file contains the generated route sets along with their length and free flow speeds. The way it is structured when opening this text file is illustrated at the bottom of the figure.

### 3.3.1 Mathematical formulation of informing model

Before route choice in the proposed framework can be determined, the route cost function which is used to determine a route's value to a traveler is described. The total utility structure which is used in the remainder of this study is

\[
U_k^{i,t} = V_k^{i,t} + \gamma_k \quad \forall k \in K
\]

In this utility function \( V_k^{i,t} \) represents an average, or systematic utility for route \( k \) (as an element of route set \( K \)), see for example Cascetta (1996). The random term \( \gamma_k \) is included.
to represent a range of unobserved influences not included in the expected traveller utility function. These unobserved factors also include errors in the modelling process by the analyst. Different distributions can be assumed but in this study $\gamma_k$ is assumed to be Gumbel distributed with variance $\frac{\pi^2}{6}$ for practical application and further route choice modelling which will be described in section 3.3.3.

In the remainder of the analyses we assume that the quality of a route is expressed through a traveller’s perception of its travel time. Furthermore, the perceived utility of a route is also negatively influenced by the uncertainty about travel times. The variance of the mean travel time estimation on part of a traveller represents a traveller’s belief in being able to correctly estimate his travel times. Thus a large variance indicates a traveller believing to be unable to accurately estimate travel times leading to a disutility for this route. The same holds for the variance of mean travel times disseminated through traffic information. With this in mind the expected utility, being the systematic part $V_{i,k}^{t,i}$ of equation 1, by a traveller $i$ for a certain route $k$ for travel time $t$ is expressed through

$$V_{i,k}^{t,i} = EU_{i,k}^{t,i} = \beta_T \cdot T_{i,k}^{t,i} + \beta_{VAR} \cdot Var(T_{i,k}^{t,i})$$

(2)

In the equation $\beta_{VAR}$ represents a traveller’s level of risk aversion. Larger levels of $\beta_{VAR}$ result in an increased weight of $Var(T_{i,k}^{t,i})$ thus representing the travellers dislike of uncertainty in travel time perception. Although this study does not include the empirical estimation of the utility coefficients, these parameters do not have to be set arbitrarily. Several empirical studies (Black & Towriss, 1993) (Noland, 1998) (Small, Noland, Chu, & Lewis, 1999) quoted in Noland & Polak (2002) have been conducted with the aim to estimate these parameters for example through the use of stated preference surveys. At the same time these studies also focussed on proving the importance of travel time variability in traveller decision making. With regard to generalization of these results one has to be careful since these results are based on specific research context and population and thus model specification. The studies nonetheless provide some indication on the ratio of $\beta_{VAR} / \beta_T$.

Ratios range from 0.55 to 3.22. These ratios merely provide a reference point on which coefficient setting for further model implementation and simulation will be based. Since the mentioned studies base the ratio on different model specifications the values ratio can not just be applied in this study.

It is assumed that a driver is able to make some approximation of travel times on the network he or she is travelling on and that this approximation is updated by travel time information provisioning en-route and experienced travel times. This analysis uses a Bayesian updating procedure by which prior perceptions are updated to posterior perceptions after receiving information during a trip.

The proposed framework for dynamics in route choice takes into account driver perception of travel time and information provisioning. Two key elements in the framework are represented by the inclusion of driver belief in his or her ability to estimate travel times and the confidence a traveller has in an information channel. The belief in ability and confidence in a traffic information channel is accounted for by the variances in perception errors of these times.

The second element is formed by route choice behaviour resulting from the updating of en-route travel time expectation. The notation in this section follows Jha et al. (1998). The variables used in this model are as follows:
$T_{k}^{i,j}$ The a priori perceived travel time by individual $i$ on time $t$ before receiving information and before the trip for $k$th path between his or her origin and destination. Since origin and destination do not vary no additional symbol is assigned to them.

$T_{k}^{i,j+1}$ Updated travel time of $T_{k}^{i,j}$ after receiving en-route traffic information (en-route updating).

$\tau_{k}^{i,j}$ The mean of $T_{k}^{i,j}$ which is the driver’s best estimate of the travel time.

$ti_{k}^{i}$ Travel time provided by a DRIP.

The a priori travel time of an individual $i$ on a time $t$ before receiving any en-route information is expressed by

$$T_{k}^{i,j} = \tau_{k}^{i,j} + \varepsilon_{1,k}^{i}$$ (3)

The a priori travel time is a distribution of $\tau_{k}^{i,j}$ as a driver’s best estimate of travel time and $\varepsilon_{1,k}^{i}$ which represents the driver’s error in perception. Different distributions can be used but the latter is assumed to be normally distributed with 0 mean and standard deviation $\sigma_{1,k}^{i}$. The normal distribution allows for further use of Bayesian travel time and perception error updating process.

### 3.3.2 En-route expected travel time updating due to information

This section describes the rules for the updating of a driver best estimate of the new expected travel time under the influence of en-route traffic information $ti_{k}^{i}$. Before setting the rule an additional assumption is made which is the following

**A4.** Users unconsciously alter presented traffic information due to his or her perception of information. This perception can be influenced by past experiences with a certain traffic information channel, in this case a DRIP. Perception can also evolve under the influence of a personal like or dislike (attitude) of the information channel. As this might seem intuitively correct, the extent to which this phenomenon takes place will differ from network location and driver target groups.

**[Implication of A4]**

In order to estimate case specific perception parameters additional future research is needed. TNO has the means to combine simulator experiments with for example stated preference research. This would provide tangible case specific data sets on which perception parameter estimation can be based.

The user perceived travel information time from a DRIP can thus be expressed by

$$tp_{k}^{i,j} = ti_{k}^{i} + \varepsilon_{2,k}^{i}$$ (4)
where $\varepsilon_{2,i,k}$ represents uncertainty on part of the driver about the mean travel time information $t_{i,k}^t$ due to factors mentioned in assumption A4 on the preceding page. Following the line of reasoning as in Eq(3), namely compatibility with a Bayesian updating process, $\varepsilon_{2,i,k}$ is also normally distributed with standard deviation $\sigma_{2,i,k}$.

The updated best estimate of the travel time after receiving travel time information from the DRIP calculated through Bayes’s theorem (Bayes, 1763) and applied by for example Chorus & Dellaert (Forthcoming) and in the different context of trip departure time also by Jha et al. (1998):

\[
\tau_{k,i}^{t,i+1} = \frac{T_{k,i}^{t,i} \cdot \text{Var}(T_{k,i}^{t,i}) + t_{i,k}^t \cdot \text{Var}(t_{i,k}^t)}{\text{Var}(T_{k,i}^{t,i}) + \text{Var}(t_{i,k}^t)}
\]

(5)

The variance of the perceived best estimate of travel time is also updated and given by

\[
\text{Var}(T_{k,i}^{t,i+1}) = \frac{\text{Var}(T_{k,i}^{t,i}) \cdot \text{Var}(t_{i,k}^t)}{\text{Var}(T_{k,i}^{t,i}) + \text{Var}(t_{i,k}^t)}
\]

(6)

The updated perceived travel time given by

\[
T_{k,i}^{t,i+1} = \tau_{k,i}^{t,i+1} + \varepsilon_{3,i,k}
\]

(7)

In previous equation (7), $\tau_{k,i}^{t,i+1}$ is provided by equation (5) and the variance of $\varepsilon_{3,i,k}$ (the latter also normally distributed since $\varepsilon_{1,i,k}$ and $\varepsilon_{2,i,k}$ are assumed normally distributed) is provided through equation (6).

“In words: Updated quality perceptions are a weighted average of prior beliefs and observed quality. Weights reflect perceived reliability of prior beliefs and observations, respectively: when the traveller distrusts (trusts) his own observations, updated perceptions of quality are relatively close to initially anticipated quality (observed quality)” (Chorus & Dellaert, Forthcoming).

So if the perceived error in the travellers initial travel time perception is lower than the perceived error in provided route travel time information, the updated expected travel time will tend to be closer to the initial travel time perception and vice versa. The updating mechanism presented in this thesis explicitly does not consider day-to-day learning effects based on en-route experiences by drivers. The updated route utility is used to recalculate route choice in the light of newly gathered information from a DRIP. Route probabilities can be determined through a logit function as described in the following section. The use of a logit function is justified by the distribution assumption made for Eq(1).
3.3.3 Modelling route choice

Using the total utility function in Eq(1) and distribution assumption the next step is to
determine route choice by drivers. Route choice may now modelled through a logit function.
The probability of choosing route $k$ is a function of the expected route utility expressed
through Eq(2). For traveller $i$ between OD-pair $n$ the probability of choosing route $k$ as an
element of the total route set for OD pair $n$ ($k \in K_n$) is computed by

$$
\Pr\{k, \ EU^{it}_{i} \} = \frac{\exp(EU^{it}_k)}{\sum_{s \in K_n} \exp(EU^{it}_s)} 
$$

(8)

The multi nomial logit approach does nog account for overlap within route sets. This can be
adjusted for by applying a function which does account for overlap. The current
implementation uses a modified multi nomial logit route choice model which accounts for
path overlap, tt is a c-logit model. In the implemented modified route choice model the
systematic part of the utility function $V^{it}_k$ is replaced by $V^{it}_k - CF_k$ for $\forall \ k \in K_n$. The term
$CF_k$ representing the communality factor of path $k$, which accounts for the degree of
overlap with the other possible paths between Od-pair $n$. It results in the following choice
probability function

$$
\Pr\{k, \ EU^{it}_{i} \} = \frac{\exp(EU^{it}_k + CF_k)}{\sum_{s \in K_n} \exp(EU^{it}_s + CF_s)} 
$$

(9)

The way in which this overlap factor negatively influences a path's utility is fairly straight
forward, a path overlapping with other has a high communality factor resulting in lower
value of the systematic part of the utility function; thus negatively affecting the probability
that this route will be chosen from the total set. For further reading on the c-logit function
and its specification we refer to Cascetta (1996).

With regard to the implementation of the informing model and route choice determination,
the overlap represented by $CF_k$ can be dealt with in three ways. The first option takes no
additional effort and basically entails disregarding overlap and $CF_k$, thus determining route
choice probability through the simple logit form in Eq(8). This is the least desirable option
since this would essentially be a step back from the current implementation in terms of
accounting for path overlap. The second option is to maintain the current implementation of
the c-logit route choice model in which $CF_k$ is determined once at the start of a simulation
run. This means that $CF_k$ stays the same while vehicles travel over a network which results
in an overestimation of the relative overlap between paths over the distance of a path. This
over or underestimation might result in drivers sticking to same route while other sub paths
might have become an alternative. The third option is to re-estimate $CF_k$ for sub paths from
the network point after a DRIP at which an en-route route decision can be made. This would
ensure that possible evolution in the overlap of route alternatives while a vehicle is travelling
over a network is accounted for.

The latter option would result in a more elegant way of dealing with the possible change in
path overlap during a trip. However due to time budget constraints the currently
implemented second option is further included during model implementation and
experiments described in chapters 4.
3.3.4 Numeric examples of driver informing mechanism

Before conducting experiments with an implemented information learning model the mechanism is tested in excel using a fictitious case. This was primarily done for the researches own insight but also clarifies the effect of the informing model to the reader of this report.

Values of $\beta$ coefficients in the utility function

Considering the situation of a pair of route alternatives of which one is considered slightly faster on average and considered relatively safe because it has been used more frequently and a route which is slightly slower on average and considered relatively riskier. With travel time (TT) itself becoming less important and the weight of travel time uncertainty (represented through the perceived travel time variance) becoming more important, a logit model as in equation (8) leads to a larger probability of choice for the less risky route.

The hypothetical situation which is analyzed is an OD-pair with two route alternatives. Route A has a TT of 400 seconds and variance 1600 seconds$^2$ ($\sigma$ is assumed 10% of TT, thus 40 seconds) and route B has a TT of 500 seconds and variance 2500 seconds$^2$ ($\sigma$ is assumed 10% of TT, thus 50 seconds) seconds. As was mentioned It is expected that while the ratio $\beta_{VAR}/\beta_T$ increases the route choice share for route B diminishes. The following table and figure were computed through an excel calculation. Initial $\beta_T$ was set at -0.0007 and was kept constant as the ratio increased from 0.

Table 3-1 Route choice probabilities

<table>
<thead>
<tr>
<th>Ratio b2/b1</th>
<th>0</th>
<th>0.2</th>
<th>0.4</th>
<th>0.6</th>
<th>0.8</th>
<th>1.0</th>
<th>1.2</th>
<th>1.4</th>
<th>1.6</th>
<th>1.8</th>
<th>2.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route A</td>
<td>0.517</td>
<td>0.549</td>
<td>0.58</td>
<td>0.61</td>
<td>0.64</td>
<td>0.668</td>
<td>0.696</td>
<td>0.722</td>
<td>0.746</td>
<td>0.769</td>
<td>0.791</td>
</tr>
<tr>
<td>Route B</td>
<td>0.483</td>
<td>0.451</td>
<td>0.42</td>
<td>0.39</td>
<td>0.36</td>
<td>0.332</td>
<td>0.304</td>
<td>0.278</td>
<td>0.254</td>
<td>0.231</td>
<td>0.209</td>
</tr>
</tbody>
</table>

The results are displayed graphically in the next figure.

Figure 3.2 Route choice probabilities

The horizontal axis mentions the $\beta_{VAR}/\beta_T$ ratio and vertical axis choice probability for both routes. In this case we observe a slight convex development of route choice probability. This is caused by the arbitrarily set low initial value of $\beta_T$. If this value had been set higher we would have expected an increasingly convex shape of the route choice development. This means that with increasing driver risk averseness and thus importance of travel time uncertainty route choice for a riskier route diminishes.
Influence of uncertainty through the magnitude of travel time variance

The same estimation for the perceived uncertainty in the utility function can be provided. With other components remaining constant, a smaller perceived uncertainty of a route ought to lead to a positive change in route choice of this route, since the expected utility function assumes risk averseness. The ratio b2/b1 is set to 1.2 and is not changed during the test range of travel time variance of route B. The effect of a negative change in travel time variance is again expected to show a diminishing positive increase of route choice for the "reliable" route A.

**Table 3-2 Route choice probabilities**

<table>
<thead>
<tr>
<th>Var B (sec)</th>
<th>0</th>
<th>100</th>
<th>400</th>
<th>900</th>
<th>1600</th>
<th>2500</th>
<th>3600</th>
<th>4900</th>
<th>6400</th>
<th>8100</th>
<th>10000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route 1</td>
<td>0.219</td>
<td>0.233</td>
<td>0.281</td>
<td>0.373</td>
<td>0.517</td>
<td>0.696</td>
<td>0.852</td>
<td>0.945</td>
<td>0.984</td>
<td>0.996</td>
<td>0.999</td>
</tr>
<tr>
<td>Route 2</td>
<td>0.781</td>
<td>0.767</td>
<td>0.719</td>
<td>0.627</td>
<td>0.483</td>
<td>0.304</td>
<td>0.148</td>
<td>0.055</td>
<td>0.016</td>
<td>0.004</td>
<td>0.001</td>
</tr>
</tbody>
</table>

The results are displayed graphically in the next figure.

![Figure 3.3 Route choice probabilities](image)

The informing mechanism during information provisioning

We continue using the previously mentioned route alternatives. At a certain point however a DRIP disseminates information about route A and its instantaneous route travel time. Route B is assumed is to have enough capacity and keeps its initial travel time estimation and initial uncertainty. The first case which is presented graphically is the presentation of information on the DRIP which results in the same route travel time as was initially estimated by a driver. In addition the drivers’ level of uncertainty about his own estimation and the travel time provided by the DRIP are assumed equal. The following table provides travel time and travel variance values accompanied by utility values and route choice shares.

**Table 3-3 Travel time and travel variance values accompanied by utility values and route choice shares**

<table>
<thead>
<tr>
<th>Route</th>
<th>Info Message</th>
<th>Updated Route</th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>400</td>
<td>A0</td>
</tr>
<tr>
<td>B0</td>
<td>400</td>
<td>A0</td>
</tr>
<tr>
<td>A</td>
<td>400</td>
<td>A1</td>
</tr>
<tr>
<td>B1</td>
<td>400</td>
<td>B1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TT</th>
<th>Var</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>400</td>
<td>1600</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Through the updating mechanism an updated mean travel time and updated travel time variance are computed for route A. It can be seen that the updated travel time remains the
same since the information reported the same route travel time as initially anticipated by the
driver. The travel time variance however is updated in accordance to equation (6). Since the
a priori and information travel time variance are equal, the updated variance is the exact
average. In its context this means the driver, through receiving information has become
more certain about the travel time variance of route A. The following graph illustrates the
theoretical development of the travel time distribution through information use by the driver.

![Figure 3.4 Development of the travel time distribution, probability on vertical axis and mean
travel time variance on horizontal axis](image)

Route A0 and route B are similarly distributed, while the distribution of route A1 indicates the
updated travel time distribution. Continuing this analysis step is to include an increasing level
of trust in provided information, its effect on the distribution and effect on route choice
probability. To this end the previous figure is again used to display the additional
distributions along with the indication of route choice shares. The latter is done by including
the choice probability of route A in table 3-4 below. For sake of readability utility values have
been excluded. The black arrows indicate which information messages lead to the updated
route travel time and variances.

| Table 3-4 |
|-----------|-----------|-----------|-----------|-----------|
| Route     | Updated Route |
| A0 | B0 | A1 | A2 | A3 |
| TT | 400 | 400 | 400 | 400 | 400 |
| Var | 1600 | 1600 | 800 | 533,33 | 399,99 |
| Probability | 0.5 | 0.5 | 0.662 | 0.71 | 0.733 |
| Info Message | TT | Var |
| TT | 400 | 400 | 400 |
| Var | 1600 | 800 | 533,33 |

The resulting travel time distributions are presented in next figure 3.6.
Figure 3.5 Development of the travel time distribution, probability on vertical axis and mean travel time variance on horizontal axis

We see that with a decreasing level of travel time information uncertainty about route A its probability density increases and moves closer to the mean. This overall illustrates an increasing level of attractiveness of this route when keeping all other factors constant. Additional examples could have been provided, a logical next being a situation in which level of uncertainty about a driver’s own expectation and that of provided information have an identical variance but different mean travel time. The resulting updated travel time then becomes the average of the driver’s own expectation and travel time provided by the DRIP.

3.4 Discussion

This chapter proposes a driver informing model. Choice for this particular model is based on the observation that the current way of modelling route choice behaviour does not incorporate driver evaluation of provided travel time information. We choose the route of modelling the information model within the existing route choice model which is deemed sufficient. Its basis is driver utility maximization while drivers are considered to be risk averse, they dislike travel time uncertainty. The latter holds for example commuters but less so for leisure drivers. This is also something to consider in future research as in this study a risk averse commuter with limited knowledge of the road network was chosen as the information end user. Other end user classes or mixing of classes bring the need to reconsider the ratio of used utility coefficients as this determines the level of risk averseness of a driver.

Some of the assumptions made in this phase clearly put limitations on the remainder of this report and future research activities. The most important assumption about modelled route choice is that information is assumed to only influence en-route route choice behaviour. This is related to this study taking into account travel time information from DRIPs, however in practise information can also have an effect when a driver reaches his destination and makes an evaluation afterwards. As a considerable amount of assumptions have been made until now, influences of information apart from en-route would add to this and overcomplicate the goal of this study. It is strongly advised however to take this and other mentioned assumptions into consideration in future research depending on the goal of the study.
3.5 Integrating driver informing into ITS Modeller

This section describes the implementation of the informing model as proposed in the previous chapter. The model is implemented in the ITS Modeller plug-in using java coding. Coding for the implemented driver information model can be found in annex 2. After the proposed model was discussed at TNO a number of additional limitations were identified. The consequences of these limitations are discussed in the following sections.

3.5.1 Constraints concerning implementation

The first limitation is caused by computer calculation power needed to perform travel time calculation for all individual drivers. This process involves computing a new distribution for travel times resulting from the drivers’ learning mechanism. Even without the informing mechanism implemented route choice and traffic analyses performed on realistically modelled networks is run at real time speed. It was deemed infeasible to fully implement individual travel time computation since on a realistic network this would cause computation time to increase a lot. The computational rules of the driver informing model are followed until the drawing of travel times from the updated driver travel time distribution. This means that drivers are not assigned individually drawn travel times, which would have been the desired situation. In reality every driver estimates his own travel time based on his own estimation under influence of travel time information from a DRIP. Instead the newly computed average travel time and standard deviation are used by all drivers having that specific route in their route set as long as the traffic information message is active. Effectively all drivers in sending range of the drip, which by default is the link on which it is modelled, execute the same update method and this update is valid until a new DRIP information update which takes at least 5 minutes. This is a clear modelling limitation since the driver informing model was proposed at the individual driver level. The effects this limitation has on simulation outcomes compared to the ideal situation is difficult to estimate, however for the 5 minute intervals this leads to homogenous route choice behaviour for the specific group of drivers. Effects at link level through put performance can be either positive when this group of drivers diverts to an empty link/route. However if a destination link is already close to capacity and additionally receives the group of diverting drivers this would probably lead to worse performance then if modelled at the individual level.

The second limitation is that, all link travel times and variances for the links composing a route are added together to attain the total distribution. This would be fine if link travel times are independent and not correlated, however in practice this is often not the case. Especially during peak hours or at bottlenecks traffic loads can cause recurring queues. These queues can spill back also causing delays up stream of the queue to drivers not necessarily taking the blocked route. This causes some correlation between route travel times for different routes. The implementation in this study does not take into account these link and route travel time correlations. With regard to applicability of the current model implementation we have to take into account this limitation. Practically this means the model is better suited for analysis of for example rural and motorway settings containing relatively long link lengths. Latter results in lower correlation between links. At same time the model is also applicable to traffic circumstances without congestion during which correlation between links also is low. From a traffic management point of view however the latter case is not a typical situation in which travel time information is necessary.
4 Testing and simulation

In this chapter research question *RQ3 What are the route choice effects of the proposed driver informing model?* is answered. In order to answer this question the implemented driver informing model is tested and an experimental setup is provided. Experiments are performed as a set of scenarios with varying scenario characteristics.

4.1 Testing information model

Verification of the implemented model starts with testing the model on a simple network and checking if model outputs are consistent with expectations. The network consists of 34 nodes, these provide network connection points at which links can be attached. The network is completed by 70 links which form the road infrastructure connecting the nodes and origin and destination zones. There is a total of 8 zones which act as generation and attraction points for traffic. The network is displayed in the next figure, the numbers accompanying the links act as a reference to the specific links throughout the rest of this chapter.

![Network with link numbers and route alternatives indicated](image)

*Figure 4.1 Network with link numbers and route alternatives indicated*

Table 4-1 on the next page summarizes characteristics of the two routes. The routes are described by their link numbers, link length in meters, maximum link speeds in km/h and total route lengths.
Table 4-1 Route North and South characteristics

<table>
<thead>
<tr>
<th>Route name</th>
<th>Link number</th>
<th>Length [m]</th>
<th>Max speed [km/h]</th>
<th>Route length [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route South</td>
<td>1</td>
<td>100</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>500</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>500</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>2000</td>
<td>120</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>2000</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>1000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>2000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>700</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>100</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>Route North</td>
<td>1</td>
<td>100</td>
<td>80</td>
<td>9900</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>500</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>500</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>2000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>1000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>2000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>2000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>1000</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>700</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>100</td>
<td>60</td>
<td></td>
</tr>
</tbody>
</table>

The main difference between the two routes is that route South is modelled as a faster route alternative through the use of highway sections. These highway sections have a maximum speed of 100 and 120 km/h. This results in different free flow travel times. Route South has a free flow travel time of 411 seconds, route North has a free flow travel time of 459 seconds. Both routes have the same origin and destination and there is no intersection signalling.

Test and simulation runs are performed on a Windows XP pc with a 3 GHz dual core processor. A run with traffic generated on the two routes using a 3 hour peak period and network cool down results in a run time of approximately 8 to 15 minutes. Run time depends on calculations and statistics which the ITS Modeller has to perform and increases with the number of vehicles on the network.

4.2 Experimental set-up

Before simulating different scenarios with varying levels of driver uncertainty and information provisioning, default values for the utility coefficients $\beta_T$ and $\beta_{VAR}$ need to be found. The default values form a reference value with which future analyses can be performed. Ideally these default values should not have to be changed, and at least lie in a range for which plausible route choice behaviour is expected.

Demand

During scenario simulation a departure profile is applied to represent a morning peak period of three hours. This peak period starts at 07:00:00 in the morning and ends at 10:00:00. Figure 4.2 on the next page displays the morning departure profile for the network. It includes the cumulative departures measured in numbers of drivers and the departure rate in travellers per hour.
In accordance with assumption A1 in chapter 3 route choice effects on driver departure times and thus effects on the peak departure profile are excluded. In reality this would most likely be different but as stated this is one of the assumptions under which the driver information model is proposed.

**DRIP and Incident**
The next figure again illustrates the used network with the links monitored by the modelled DRIP in scenarios 3, 4, 7 and 8. During the information scenarios *information is only provided for the non overlapping links* of route South. For an unexplainable reason to the author the modelled DRIP was not able to monitor link 7. This means only information updates are provided for links 4, 5, 6 and 8. Due to time budget constraint this modelling error was not solved. The most likely cause is a wrongly entered link reference in the modelled DRIP, indicating researcher error. A second possibility is that the ITS Modeller does not correctly handle the reference to link 7. This seems to be the case as the reference to link 7 is modelled analogous to the other monitored links. The consequence of exclusion of this link in information provisioning is that it results in underestimation of route cost for route South. If a queue develops and spills back the exclusion of link 7 in a route cost update means the computed delay on this link is not accounted for in the total route cost. In turn this leads to a more positive travel time outlook and subsequent cost to drivers thus resulting in a more attractive route South than really is the case.

Following picture 4.2 also indicates the network location of the DRIP on link 2 and the incident located on link 7. The incident is modelled to start at 7:02 and takes to 2 hours to clear. Passing speed for traffic on the free lane is set at 10 km/h. The specific duration and location of the incident are chosen in order to start queuing earlier than in the reference situation without an incident. In addition this location results in a relative large section of route South upstream of the incident being affected by queuing. These considerations increase the chance that driver information updates result in altered route choice behaviour. This aids in the goal of showing the effect of the driver information updates and route choice behaviour.

**Driver**
For all following tests and scenario analyses we consider a commuter travelling from home to work being on this part of the road network for the first time. He is unfamiliar with route alternatives and in case of information provisioning attaches extra value to information about route travel times and thus disutility. It should be noted that this driver type acts as a hypothetical user case in order to illustrate the implemented informing model.
4.2.1 Determining default utility coefficient values

Tests in this section include relatively short simulated times. Since no information is provided, no learning effect yet takes place and link and route costs remain the same throughout the tests this is justified. Given the fact that an indication for a range was found in chapter 3, albeit only an indication, this part of the study continues with finding values for $\beta_T$ and $\beta_{VAR}$. It is important for several reasons, the first being that with the availability of default values a future user of the model does not have to determine these himself increasing user friendliness. Secondly we need to find these values in order to continue with scenario analysis in following parts of this chapter in which the effect of provisioning information to the drivers with varying levels of travel time uncertainty is investigated. At the end of this section insight is gained in the effect of these values on route shares given the network and traffic demand. Furthermore after this section insight is gained in the range in which these values lie. Based on this insight it is then possible to qualitatively predict the effect on route choice if $\beta_{VAR}$ and $\beta_T$ are out of the range.

Setting $\beta_T$ to 1 and $\beta_{VAR}$ to 0 is used as a reference case. This results in route choice behaviour which is the same as in the original route choice implementation, thus only based on travel times. Adding mean travel time variance should lead to fewer drivers choosing the slower route North as the mean travel time variance is assumed to be 10% of the free flow link travel times. We expect the need to adjust the range of betas in order to compensate for increasing route costs due to inclusion of mean travel time variance. The resulting route shares are reported in following table 4-2.
Table 4-2 Route share overview

<table>
<thead>
<tr>
<th>$\beta_T$</th>
<th>$\beta_{VAR}$</th>
<th>Route</th>
<th>Vehicles</th>
<th>Share</th>
<th>Route cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>South</td>
<td>2397</td>
<td>0.591</td>
<td>406</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>South</td>
<td>2733</td>
<td>0.851</td>
<td>644</td>
</tr>
<tr>
<td>0.001</td>
<td>0.001</td>
<td>South</td>
<td>476</td>
<td>0.149</td>
<td>766</td>
</tr>
<tr>
<td>0.01</td>
<td>0.01</td>
<td>South</td>
<td>1992</td>
<td>0.446</td>
<td>0.644</td>
</tr>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>North</td>
<td>2477</td>
<td>0.554</td>
<td>0.766</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>South</td>
<td>2501</td>
<td>0.560</td>
<td>7.661</td>
</tr>
<tr>
<td></td>
<td></td>
<td>North</td>
<td>2046</td>
<td>0.463</td>
<td>64.92</td>
</tr>
<tr>
<td></td>
<td></td>
<td>South</td>
<td>2046</td>
<td>0.463</td>
<td>64.92</td>
</tr>
<tr>
<td></td>
<td></td>
<td>North</td>
<td>2371</td>
<td>0.537</td>
<td>76.61</td>
</tr>
<tr>
<td></td>
<td></td>
<td>South</td>
<td>2697</td>
<td>1</td>
<td>6439</td>
</tr>
<tr>
<td></td>
<td></td>
<td>North</td>
<td>0</td>
<td>0</td>
<td>7661</td>
</tr>
</tbody>
</table>

Figure 4.3 shows the output in a histogram. Route shares for the reference case are not included.

![Figure 4.3 Route share development](image)

The figure indicates relative insensitivity for beta values ranging from 0.001 to 0.1. From 0.1 to 1 however a clear change is seen in route choice probability pointed out by the black arrow. This change is caused by the absolute difference in route costs as a result of increasing $\beta_T$ and $\beta_{VAR}$ in order of magnitude from 0.1 to 1. The route costs enter the c-logit model mentioned in chapter 3 and subsequently result in a clear increased route share of route South. It indicates a plausible magnitude for the beta coefficients including travel time variance but excluding the effect of travel time information. Further focus is put on the identified magnitude and additional simulation runs are performed to identify a plausible magnitude for the beta coefficients. The results are reported in the following figure 4.4.
The figure indicates that the flipping point in favour of route South lies between beta values 0.2 and 0.3 (share route South > share route North) for which we assume 0.3. After this step the next issue arises, namely concerning the earlier assumption that mean travel time variance in the utility function plays a more important role than travel time itself. An additional step is to find an appropriate ratio between $\beta_{\text{VAR}}$ and $\beta_T$. With the stated assumption the ratio should comply with $\beta_{\text{VAR}} / \beta_T > 1$. $\beta_{\text{VAR}}$ is set at 0.3 and the ratio is increased, the results for this step are presented in the following table 4-3 and figure 4-5. This step results in coefficient values which conform to the ratio assumption and lead to route shares deemed plausible for our test network. Plausibility results from the fact that route South is modelled with faster highway links representing a stretch of motorway with maximum speeds of 120 km/h, whereas route North is modelled with a maximum speed of 80 km/h overall. Referring to the chosen driver type we should at least see a larger share of drivers choosing route South.

### Table 4-3 $\beta_{\text{VAR}} / \beta_T$ ratio and route share

<table>
<thead>
<tr>
<th>Ratio $\beta_{\text{VAR}} / \beta_T$</th>
<th>1</th>
<th>1.2</th>
<th>1.4</th>
<th>1.6</th>
<th>1.8</th>
<th>2.0</th>
<th>2.2</th>
<th>2.4</th>
<th>2.6</th>
<th>2.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route South</td>
<td>0.521</td>
<td>0.556</td>
<td>0.576</td>
<td>0.598</td>
<td>0.632</td>
<td>0.656</td>
<td>0.673</td>
<td>0.688</td>
<td>0.7</td>
<td>0.717</td>
</tr>
<tr>
<td>Route North</td>
<td>0.479</td>
<td>0.444</td>
<td>0.424</td>
<td>0.402</td>
<td>0.368</td>
<td>0.344</td>
<td>0.327</td>
<td>0.312</td>
<td>0.3</td>
<td>0.283</td>
</tr>
</tbody>
</table>
A plausible larger share of drivers choose route South at a $\beta_{VAR}/\beta_T$ ratio of 1.6, with $\beta_T = 0.3$ and $\beta_{VAR} = 0.48$. At this ratio 59.8% of the drivers choose the perceived “better” route South. Since this is a hypothetical case study the decision for a ratio of 1.6 is made somewhat arbitrarily. It is supported however by the fact that route South is modelled with faster highway links representing a stretch of motorway with maximum speeds of 120 km/h, whereas route North is modelled with a maximum speed of 80 km/h overall. The assumption here is that the unfamiliar driver prefers a faster highway route than the slower alternative on a secondary part of the network.

### 4.3 Performing experiments

In this section the informing is applied in different scenarios. For this study reference scenarios provide a starting point to which alternative scenarios can be compared. In section 4.2 we already used a reference scenario, which we also do in this section. There is one addition however, the scenarios in the experimental part are compared to two reference scenarios. The difference between the two reference scenarios is the level of driver uncertainty.

#### 4.3.1 Scenario selection

The selected scenarios reflect for a large part reflect analyses choices and assumptions made earlier in this report and are performed to illustrate and analyse the effect of the assumed driver informing model. In this section the same network is used as in section 4.2. The selected scenarios are constructed through a few scenario variables. These scenario variables are driver uncertainty about his own mean travel time estimation, driver uncertainty about mean time travel time provided by a DRIP, whether information is provided or not and the occurrence of an incident.

The current implementation of information use by drivers assumes a probability for information use and route travel cost updating. This probability is set at 1 by default, resulting in 100% of drivers updating their expected route cost based on traffic information. For performing experiments and interpreting effects of the proposed informing model it is deemed unnecessary to include this probability as a variable in the experimental scenarios. The argumentation here is that this study does not investigate this particular parameter since in reality it is affected by many factors, some characteristic of drivers others externally, we leave the default information use probability at 1 for the remainder of the experiments. The consequence of less than 100% compliance is that drivers despite information provisioning do not update their initial route cost estimation and keep to their initial route choice. This results in less drivers potentially switching route and thus a lower effect of
information provisioning. The scenarios which we use in the following sections are represented in table 4-4.

Table 4-4 Simulation scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Driver uncertainty of own mean travel time</th>
<th>DRIP active</th>
<th>Driver uncertainty of DRIP mean travel time</th>
<th>Incident</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>low</td>
<td>high</td>
<td>No</td>
<td>yes</td>
</tr>
<tr>
<td>1</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>7*</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>

During these scenarios we use the following levels of driver uncertainty.

Table 4-5

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Sigma1 Own</th>
<th>Sigma2 Info</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>X</td>
</tr>
<tr>
<td>2</td>
<td>7.5</td>
<td>x</td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>X</td>
</tr>
<tr>
<td>6</td>
<td>7.5</td>
<td>x</td>
</tr>
<tr>
<td>7</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>7*</td>
<td>15</td>
<td>10</td>
</tr>
<tr>
<td>8</td>
<td>30</td>
<td>10</td>
</tr>
</tbody>
</table>

Scenarios and effect of information and route choice behaviour are evaluated by indicators on individual driver, route and link levels. These include route shares based on total vehicle count, route travel times and route cost plots also on individual vehicle level and mean speed and average travel times for selected links. We now continue with the analysis of scenarios for an initially confident driver.
4.3.2 Scenarios for a confident driver

Preliminary tests showed that with the given traffic demand queues form on route South which in some situations spill back to the node at which drivers can choose their route. We therefore choose to report statistics of links 4 and 11. The third link which is included in the simulation results is link 7. It is included since it is the link at which an incident is placed. The next figure illustrates the selected links marked in red. It also indicates the link travel time variances in red and green.

Before continuing to scenario results some important notions have to be made. The first one concerns the link variances used during scenario simulation and driver information updates. Instead of using a percentage of free flow link travel times as the mean travel time variance a variance is set per route link. The decision to set variances at the chosen values was done in order to maintain analysis oversight while describing effects of the driver informing model. It does not affect the functioning of the driver information model. By doing so however the link mean travel time variance now becomes dependant on the number of links, while in reality drivers do not think in terms of links but would in travel times or route length for example. This assumption has to be taken into account in future research since addition, removal or division of links by the researcher now also affects route mean travel time variance. Latter should then be reassigned in the route cost function code again to use a percentage of initial estimated travel time.
Before reporting the simulation result with provisioning of information the parameters which are used when the informing mechanism is activated are provided in the next table.

### Table 4-6 Driver uncertainty parameter values

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Sigma1 own</th>
<th>Sigma2 info</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>7</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>7*</td>
<td>15</td>
<td>10</td>
</tr>
</tbody>
</table>

For links which are included in an information update we apply added weight to the utility variables travel time and variance. The assumption here is that the weight of the disutility coefficients of these links increases as information is provided to our unfamiliar commuter. This commuter appreciates this insight in route information and thus we increase beta coefficients by a factor 2.

#### 4.3.3 Simulation results

All scenarios comprise of six runs, each time with a varying demand seed. This seed results in slightly different vehicle release rate each time a scenario is run. On average release behaviour between all scenarios is kept stable by using the same seeds for all runs. Table 4-6 shows the route choice statistics for scenarios 1, 4, 5, 7 and 7*.

### Table 4-7 Route choice statistics for scenarios 1, 4, 5, 7 and 7*

<table>
<thead>
<tr>
<th>Route</th>
<th>Scenario 1</th>
<th>Scenario 4</th>
<th>Scenario 5</th>
<th>Scenario 7</th>
<th>Scenario 7*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vehicles</td>
<td>Share</td>
<td>Vehicles</td>
<td>Share</td>
<td>Vehicles</td>
</tr>
<tr>
<td>1</td>
<td>39945</td>
<td>0.66</td>
<td>26409</td>
<td>0.44</td>
<td>39945</td>
</tr>
<tr>
<td>2</td>
<td>20218</td>
<td>0.34</td>
<td>33754</td>
<td>0.56</td>
<td>20218</td>
</tr>
</tbody>
</table>

We see the same route choice shares in pairs for scenarios 1-5 and 4-7, in which travel time variances were set equal. The aggregated simulation results for the five scenarios are reported in the following table 4-7.

### Table 4-8 Aggregated simulation results

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Scenario 1 (reference)</th>
<th>Scenario 4</th>
<th>Scenario 5</th>
<th>Scenario 7</th>
<th>Scenario 7*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total nr of vehicles</td>
<td>60163</td>
<td>60163</td>
<td>60163</td>
<td>60163</td>
<td>60163</td>
</tr>
<tr>
<td>Travel time [hours]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Total</td>
<td>40538.56</td>
<td>14410.27</td>
<td>36795.74</td>
<td>14674.03</td>
<td>14432.05</td>
</tr>
<tr>
<td>• Average</td>
<td>0.67</td>
<td>0.24</td>
<td>0.61</td>
<td>0.24</td>
<td>0.24</td>
</tr>
<tr>
<td>Travel distance [km]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Total</td>
<td>595613.7</td>
<td>595613.7</td>
<td>595613.7</td>
<td>595613.7</td>
<td>595613.7</td>
</tr>
<tr>
<td>• Average</td>
<td>9.9</td>
<td>9.9</td>
<td>9.9</td>
<td>9.9</td>
<td>9.9</td>
</tr>
<tr>
<td>Delay all veh. [hours]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Total</td>
<td>33604.46</td>
<td>7206.77</td>
<td>29772.71</td>
<td>7468.81</td>
<td>7224.04</td>
</tr>
<tr>
<td>• Average</td>
<td>0.56</td>
<td>0.12</td>
<td>0.49</td>
<td>0.12</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Next we continue reporting scenario outcomes. The first scenario comparison is aimed at isolating route choice effect solely on the difference of driver uncertainty.
Comparison 1: Scenario 7 - Scenario 7* [Difference in driver uncertainty, only learning effect]

In this comparison both scenarios include provisioning of information and include an incident. This comparison is included to illustrate the effect of the information learning model itself with different levels of driver uncertainty about travel times. To be more precise in scenario 7 the driver is more certain about his own travel time estimation than that provided by a DRIP. In scenario 7* the opposite is the case and the driver has more trust in the travel time estimation of the DRIP while all other factors are kept constant. Any difference in performance indicators between the two scenarios is contributed to higher updated route costs in case of the uncertain driver.

Overall network performance shows little difference between the two scenarios. A small difference can be seen in the route shares. In scenario 7 route South is taken by 44% of the drivers which is 43% in scenario 7*. Further investigation of indicators shows additional information about the effects of the informing model on route choice and travel times. The route travel time plots on the next page indicate that the development of travel time dispersion of route South in scenario 7 is slightly less homogeneous compared to the development of dispersion in scenario 7*. This observation is supported by taking into account the box plots for the two scenarios. These show that in scenario 7 the median is 1107 seconds, which is 1087 seconds in scenario 7*. Travel time dispersion through the inter quartile range (IQR) as well as the total range of travel times also proves to be slightly different. IQR is 274 seconds for scenario 7* and 304 seconds for scenario 7. This indicates that 50% of all drivers choosing route South experience travel times which lie in a smaller bandwidth than in scenario 7. The overall travel time range is 1515 seconds in scenario 7* and 1609 seconds in scenario 7. These travel time dispersion characteristics lead to an average travel times for route South of 1105 and 1135 seconds for scenario 7* and 7 respectively. The average travel time of route North is the same for both scenarios. Travel time dispersion characteristics indicate that in case of higher driver trust in DRIP information travel times lie in a smaller bandwidth and the distribution is such that it leads to a lower overall average travel time. It must be stated however that these differences are relatively small and no test of significance was performed. The graphical representation of experienced travel times provides an additional face validity check on the slightly different travel time dispersion.

Since the goal of this comparison is to illustrate the effect of different levels of uncertainty and that the driver informing model functions as intended route cost development is taken into consideration. Route cost evolution should show different costs with every information update and driver informing sequence. Scenario 7* should display higher costs with every update since the drivers updated mean travel time lies closer to the information provided by the DRIP and updated mean variance is the same in both. Route cost development for both scenarios is shown in following figure 4.8.

Functioning of the update mechanism is indeed supported by the higher costs in scenario 7* although the absolute differences are not large. In scenario 7 three information updates occur. The first one raises route cost from 229.8 to 240.66. The second update increases route cost from 240.66 to 248.71 as queuing continues. The third and last update takes place when queuing only takes place on link 8 and stays there. Route cost is updated downwards from 248.71 to 237.85.

In case of scenario 7* also three information updates occur. The first one raises route cost from 229.8 to 243.35. The second update increases route cost from 243.35 to 254.09 as

---

2 IQR represents the middle 50% of measurements in the data set
queuing continues. The third and last update takes place when queuing only takes place on link 34 and stays there. Route cost is updated downwards from 254.09 to 240.54. This comparison does not prove a significant difference between certain and uncertain driver. A majority of the runs however indicate better travel time dispersion characteristics in case of the uncertain driver. This is the result of expected travel time updates being closer to the DRIP estimation in turn resulting in slightly more uncertain drivers diverting.

Figure 4.8 Scenario 7 on the left, scenario 7* on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.
<table>
<thead>
<tr>
<th>Labels</th>
<th>Route South</th>
<th>Route North</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>368</td>
<td>406.5</td>
</tr>
<tr>
<td>Q₁</td>
<td>989</td>
<td>628</td>
</tr>
<tr>
<td>Median</td>
<td>1107</td>
<td>662.5</td>
</tr>
<tr>
<td>Q₃</td>
<td>1293</td>
<td>723</td>
</tr>
<tr>
<td>Max</td>
<td>1976.5</td>
<td>826.5</td>
</tr>
<tr>
<td>IQR</td>
<td>304</td>
<td>95</td>
</tr>
<tr>
<td>Upper Outliers</td>
<td>75</td>
<td>0</td>
</tr>
<tr>
<td>Lower Outliers</td>
<td>90</td>
<td>369</td>
</tr>
<tr>
<td>Mean</td>
<td>1135.07976</td>
<td>661.9774011</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Labels</th>
<th>Route South</th>
<th>Route North</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>368</td>
<td>406.5</td>
</tr>
<tr>
<td>Q₁</td>
<td>966</td>
<td>627</td>
</tr>
<tr>
<td>Median</td>
<td>1086.5</td>
<td>662.5</td>
</tr>
<tr>
<td>Q₃</td>
<td>1239.625</td>
<td>715.5</td>
</tr>
<tr>
<td>Max</td>
<td>1882.5</td>
<td>843.5</td>
</tr>
<tr>
<td>IQR</td>
<td>273.625</td>
<td>88.5</td>
</tr>
<tr>
<td>Upper Outliers</td>
<td>109</td>
<td>0</td>
</tr>
<tr>
<td>Lower Outliers</td>
<td>110</td>
<td>417</td>
</tr>
<tr>
<td>Mean</td>
<td>1105.188761</td>
<td>660.8829316</td>
</tr>
</tbody>
</table>

Figure 4.6 Box plots for scenario 7 on the left scenario 7* on the right accompanied by box plot values
Comparison 2: Scenario 1 - Scenario 5 [Influence of incident]

Scenario 1 and scenario 5 differ in the occurrence of the modelled incident. Scenario 1 is considered the reference point in this section. The driver throughout this section is considered certain about his mean travel time estimation. The only difference between these two scenarios is the presence of the incident on link 7, effectively resulting in the added effect of an incident on network performance.

Route choice statistics show that in both scenarios routes South and North receive equal amounts of vehicles, which is as expected since no information is provided and traffic demand follows the same departure profile over all scenarios. Route South and North attract 66% and 34% of the vehicles respectively. Overall network performance shows some remarkable results, namely indicating better performance during the incident scenario. In the latter total travel time is lower by roughly 4000 vehicle hours. This result in lower total vehicle delay hours and a lower average delay per driver. Further link analysis offers an explanation for this seemingly contradictory result.

The route cost overviews indicate that there is a larger spread in travel times over time in the reference scenario 1. The incident causes drivers to experience a maximum of roughly 5200 seconds on route South whereas quite a number of drivers experience travel times up to 6000 and even as high as 6500 seconds when the incident does not occur. Boxplot analysis on the travel times per route shows that indeed that the median travel time for route South is lower in the incident scenario. At the same time travel time dispersion through the inter quartile range (IQR) as well as the total range of travel times time are smaller. IQR is 1575 and 1419.5, overall travel time range is roughly 6200 and 4900 seconds for scenario 1 and 5 respectively. This affirms the initial suspicion of higher travel time dispersion in scenario 1 for route South. This is supported by the lower average travel time for route South in the incident scenario. Route North has enough capacity to handle the traffic received in both scenarios which is supported by the small travel time dispersion and almost equal average travel time evolution. In both scenarios route North is affected by spill back. In scenario 1 this occurs from about 08:15 and 08:30 in scenario 5. The comparison continues on the next page providing additional insight at link level.
Figure 4.7 Scenario 1 on the left, scenario 5 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

Figure 4.8 Box plots for scenario 1 on the left scenario 5 on the right accompanied by box plot values.
Link performance plots on the next page show that spillback reaches link 4 earlier in case of the incident. This is as expected since the incident causes queuing to start on link 7 from 7:02. Spill back effect becomes noticeable after 60 minutes at link 4. In reference scenario 1 spill back effect is noticeable after roughly 75 minutes. Then main difference between the two scenarios is that route South is affected more in scenario 1 by the demand peak which can be seen on link 14 starting after 90 minutes. During the demand peak travel time increases which results in a clear peak in average travel times on the incident link. As a matter of fact average travel times are structurally lower in the incident scenario until the accident clears after 120 minutes.

It appears that the incident has a net positive effect on network performance. This is unexpected but the occurrence of the incident and its bottle neck effect results in a smaller queue compared to scenario 1. Queuing in scenario 1 spilled back from link 8 to link 4. In the incident scenario the queue is only present from link 7 to link 4. After the incident drivers can drive without delays as that part of the route is relatively empty. This shorter queue length has a positive effect on total travel times and delay times. We have to take into account though that drivers who physically can not enter the Paramics network from their origin are temporarily stored and released when possible. This effect is larger in the incident scenario supported by the fact that it takes 15 minutes longer in the incident scenario for all drivers to reach their destination. This temporary storage of drivers before release to the network is a clear limitation of modelling as the delay incurred during this storage is not represented in ITS Modeller statistics and leads to underestimation of realized travel and delay times.
Figure 4.9 Selected link mean speeds and average travel times
Comparison 3: Scenario 1 - Scenario 4 [Influence of DRIP]

Scenario 1 and scenario 4 are different in that drivers receive travel time information in scenario 4. Other factors are kept equal and no incident is modelled. We expect to see a clear difference in travel time dispersion for route South and resulting from different route choice behaviour. The difference results from drivers rerouting to the alternative route.

In scenario 1 route South and North attract 66% and 34% of the drivers respectively. In scenario 4 route South and route North attract 44% and 56% of the drivers respectively. Overall network performance shows better performance in case of information provisioning. With information provisioning total travel time is lower by roughly 26000 vehicle hours. This directly affects total vehicle delay hours and a lower average delay per driver. The latter for example drops to only 0.12 hours.

The route travel time plots indicate that travel time dispersion of route South in scenario 4 has decreased. At the same time the travel time distributions of route South and North lie closer to each other than in scenario 1. Information provisioning now causes drivers to only experience a maximum travel time of roughly 1600 seconds on route South. The box plots show that median travel time for route South is much lower in the information scenario. The median is now at 950 seconds as opposed to 3300 in the reference situation. Travel time dispersion through the IQR as well as the total range of travel times time are significantly smaller. IQR has become 260 seconds and the overall travel time range decreased to 1300 seconds.
Figure 4.10 Scenario 1 on the left, scenario 4 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

<table>
<thead>
<tr>
<th>Labels</th>
<th>Route South</th>
<th>Route North</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>349</td>
<td>401.5</td>
</tr>
<tr>
<td>Q₁</td>
<td>2563</td>
<td>453</td>
</tr>
<tr>
<td>Median</td>
<td>3393</td>
<td>566.5</td>
</tr>
<tr>
<td>Q₃</td>
<td>4138</td>
<td>748.5</td>
</tr>
<tr>
<td>Max</td>
<td>6523</td>
<td>905</td>
</tr>
<tr>
<td>IQR</td>
<td>1575</td>
<td>295.5</td>
</tr>
<tr>
<td>Upper Outliers</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Lower Outliers</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mean</td>
<td>3351.203132</td>
<td>603.074647</td>
</tr>
</tbody>
</table>

Figure 4.11 Box plots for scenario 1 on the left scenario 4 on the right accompanied by box plot values.

<table>
<thead>
<tr>
<th>Labels</th>
<th>Route South</th>
<th>Route North</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>349</td>
<td>403</td>
</tr>
<tr>
<td>Q₁</td>
<td>829</td>
<td>631</td>
</tr>
<tr>
<td>Median</td>
<td>950.5</td>
<td>665</td>
</tr>
<tr>
<td>Q₃</td>
<td>1088.5</td>
<td>718</td>
</tr>
<tr>
<td>Max</td>
<td>1659.5</td>
<td>841</td>
</tr>
<tr>
<td>IQR</td>
<td>259.5</td>
<td>87</td>
</tr>
<tr>
<td>Upper Outliers</td>
<td>203</td>
<td>0</td>
</tr>
<tr>
<td>Lower Outliers</td>
<td>37</td>
<td>214</td>
</tr>
<tr>
<td>Mean</td>
<td>975.4099671</td>
<td>667.8009743</td>
</tr>
</tbody>
</table>
Link analysis shows that spill back does not reach link 4 anymore in scenario 4. After the first information update queuing is actually limited to the last non overlapping link 8 on route South. With the assumed driver informing model this information update limits link and thus overall queuing drastically and results in lower route travel times on route South. We do see that the average travel time of route North increases due to the provisioning of information and subsequent increase of traffic to route North. Without information the average travel time was 603 seconds in comparison to 668 seconds under the influence of information.

Information provisioning proves to have a clear positive effect on travel time dispersion and experienced travel times. Information provisioning leads to a reduction of spillback to the route decision point on this particular network, however alleviating queuing on route South leads to a drop in average experienced travel time of route North. Influencing route choice in our hypothetical case results in a negative effect on driver experience on an other part of the network. This is a phenomenon which could also occur during information provisioning in practise. This is further elaborated on the discussion section of this chapter.
Figure 4.12 Selected link mean speeds and average travel times
Comparison 4: Scenario 5 - Scenario 7 [Influence of DRIP]
Both scenarios include the modelling of the incident on link 7. In scenario 7 however information is provided to drivers.

Under influence of information we see that drivers divert to route North. In total 44% of the drivers choose route South and 56% choose route North. This is opposed to 66% and 34% for route South and North in scenario 1. With information provisioning total travel time is lower by roughly 22000 vehicle hours. This again directly affects total vehicle delay hours and a lower average delay per driver. The latter for example drops to 0.12 hours.

The route travel time plots indicate that travel time dispersion of route South in scenario 7 has decreased. The travel time distributions of route South and North lie closer to each other than in scenario 5. Again information provisioning now causes drivers to experience a maximum travel time of roughly 2000 seconds on route South. This is an improvement with respect to the maximum travel time of 5200 in the incident scenario without information. The box plots show that median travel time for route South is lower in the information scenario. The median is now at 1100 seconds as opposed to 2700 seconds in scenario 5. Travel time dispersion through the IQR as well as the total range of travel times have decreased. IQR has become 304 seconds from 1420 and the overall travel time range decreased to 1600 seconds from 4900 seconds. The observation of route cost development over time provides an indication of the number of information updates over the course of a simulation run. Information is updated by the DRIP on three occasions. The first update occurs after queuing starts on link 7 behind the accident and reaches link 6. As this queue continues to grow despite the amount of diverting drivers the DRIP provides a second update as the queue increases in length and reaches link 5. This information update causes more drivers to divert and the queue behind the accident to decrease. Between 07:30 and 07:45 the last update occurs when queuing is only present on link 8 and 7 and as such is contained on these two links until the end of the peak period.
Figure 4.13 Scenario 5 on the left, scenario 7 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

Figure 4.14 Box plots for scenario 5 on the left scenario 7 on the right accompanied by box plot values
Given the fact that earlier observation indicated queuing between 07:30 and 07:45 to only occur on links 8 and 7, this should be represented in the link statistics for selected link 7. Indeed a decline in mean speed and average link travel time are observed from the start of the simulation. As the DRIP continues to provide information updates performance of link 7 increases after roughly 30 minutes in the peak period which corresponds to the containment of queuing on link 8 and link 7. As the incident is removed after 120 minutes in the peak period no queuing occurs on link 7 and link performance stabilizes until the end of the simulation. We also see a temporary increase in link performance of link 7 in scenario 5 after 120 minutes. This is due to the fact that the incident is removed from the network and drivers are able to continue on both lanes. This only occurs for a few minutes as drivers join the queue on link 8 which spills back and queuing again establishes itself on link 7 until the end of the simulation.
Figure 4.15 Selected link mean speeds and average travel times
Comparison 5: Scenario 4 - Scenario 7 [Influence of incident]
In this comparison both scenarios include provisioning of information. In addition to this scenario 7 also includes the modelled incident.

Under the influence of information we see that drivers divert to route South. In total 44% of the drivers choose route South and 56% choose route North under the influence of information in both scenarios. As the incident in scenario 7 affects queuing on route South further evaluation sheds light on the dispersion of travel times and effect of route choice behaviour on route and link performance.

The route travel time plots indicate that the development of travel time dispersion of route South in scenario 7 is less homogeneous compared to the development of dispersion in scenario 4. This observation is supported by taking into account the box plots for the two scenarios. These show that in case of the incident scenario the median is 1100 seconds, which is 950 seconds in scenario 4. Travel time dispersion through the IQR as well as the total range of travel times proves to be slightly different. IQR is 260 seconds for scenario 4 and 304 seconds for scenario 7. The overall travel time range is 1300 seconds in scenario 4 and 1600 seconds in scenario 7. These travel time dispersion characteristics lead to an average travel times for route South of 975 and 1135 seconds for scenario 4 and 7 respectively. The average travel time of route North is almost the same for both scenarios. With regard to information provisioning in scenario queuing is contained on links 8 and 7 with one information update between 07:00 and 07:15. This is the main difference compared to scenario 7. Route cost development indicates that queuing is contained to links 8 and 7 only after 2 expected route cost increases. This also becomes clear when taking into account link performance of link 7.
Figure 4.16 Scenario 4 on the left, scenario 7 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

Figure 4.17 Box plots for scenario 4 on the left scenario 7 on the right accompanied by box plot values.

<table>
<thead>
<tr>
<th>Labels</th>
<th>Route South</th>
<th>Route North</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>349</td>
<td>403</td>
</tr>
<tr>
<td>Q1</td>
<td>629</td>
<td>631</td>
</tr>
<tr>
<td>Median</td>
<td>950.5</td>
<td>718</td>
</tr>
<tr>
<td>Q3</td>
<td>1088.5</td>
<td>841</td>
</tr>
<tr>
<td>Max</td>
<td>1659.5</td>
<td>87</td>
</tr>
<tr>
<td>IQR</td>
<td>259.5</td>
<td>87</td>
</tr>
<tr>
<td>Upper Outliers</td>
<td>203</td>
<td>0</td>
</tr>
<tr>
<td>Lower Outliers</td>
<td>37</td>
<td>214</td>
</tr>
<tr>
<td>Mean</td>
<td>975.4099671</td>
<td>667.8009743</td>
</tr>
</tbody>
</table>
We then see a clear drop of performance of link 7 in both scenarios. As information is provided for the first time however queuing on link 7 decreases and actually dissolves in scenario 4 and is limited to link 8. In scenario 7 queuing on link 7 is not totally prevented as the accident is still present for 120 minutes while forcing a passing speed of 10 km/h. This causes the average speed on link 7 to be less than 40 km/h until 120 minutes after the start of the simulation.

In conclusion the effect of the incident and resulting queuing in these two scenarios leads to different pattern of information provisioning. Under influence of the incident expected route cost increases two times in scenario 7 due to queuing reaching upstream links 6 and 5. In scenario 4 only one information update is provided. This difference leads to a temporary higher expected route cost for route South and higher route diversion in scenario 7.
Figure 4.18 Selected link mean speeds and average travel times.
4.3.4 Scenarios for an insecure driver

We continue to use the same network and same traffic demand matrix. Scenario 4 uses a higher level of uncertainty by increasing the link travel time variances. This is represented by a travel time variance of 56.25 seconds (standard deviation of 7.5 seconds) for all overlapping links and the non overlapping links of route South. All the non overlapping links of route North get a travel time variance of 81 seconds (standard deviation of 9 seconds). This is illustrated in the next figure.

![Network with link travel time variances](image)

We expect an initial larger share of drivers choosing route 1 in all scenarios compared to the scenarios in the previous section. The reason for this expectation the fact that the absolute difference in total route cost increases increased. For readability purposes and to illustrate the effect of information provisioning traffic statistics fro the same links are reported. Additional information is provided by taking a closer look at computed route costs as these develop over time under influence of travel time information and driver information learning. The expected increase in link performance on the mentioned links will be indicative of information provisioning and information learning behaviour by drivers.

Before reporting the simulation result with provisioning of information the parameters which are used when informing mechanism is activated are provided in the next table.

Table 4-9 Driver uncertainty parameter values

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Sigma1 own</th>
<th>Sigma2 info</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>30</td>
<td>10</td>
</tr>
<tr>
<td>8</td>
<td>30</td>
<td>10</td>
</tr>
</tbody>
</table>

For links which are included in an information update we apply added weight to the utility variables travel time and variance. The assumption here is that the weight of the disutility coefficients of these links increases as information is provided to our unfamiliar commuter. This commuter appreciates this insight in route information and thus we increase beta.
coefficients by a factor 4, since we assume the driver is initially uncertain about his travel time estimation he attaches more value to information than in the previous section.

First with an initial higher link uncertainty we assume that this uncertainty increases in the presence of information. At the same time under these circumstances of high driver uncertainty the utility weight of those parts (links) of the route which are monitored are also increased. This results in the higher sigma (and thus variance) values in scenario 3 and 8 combined with a high weight of the utility coefficients. Scenario 4 and 7 also receive higher weights for the utility coefficients, however these were set lower as drivers had higher confidence in their own travel time estimation.

4.3.5 Simulation results

Table 4-9 shows the route choice statistics for scenarios 2, 3, 6 and 8 based on all simulation runs per scenario.

Table 4-10 Route choice statistics for scenarios 2, 3, 6 and 8

<table>
<thead>
<tr>
<th>Route</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 6</th>
<th>Scenario 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vehicles</td>
<td>Share</td>
<td>Vehicles</td>
<td>Share</td>
</tr>
<tr>
<td>1</td>
<td>46615</td>
<td>0.77</td>
<td>26800</td>
<td>0.45</td>
</tr>
<tr>
<td>2</td>
<td>13548</td>
<td>0.23</td>
<td>33363</td>
<td>0.55</td>
</tr>
</tbody>
</table>

In addition to these total route shares the scenarios score as following on the network performance parameters.

Table 4-11 Network performance parameters

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Scenario 2 (reference)</th>
<th>Scenario 3</th>
<th>Scenario 6</th>
<th>Scenario 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total nr of vehicles</td>
<td>60163</td>
<td>60163</td>
<td>60163</td>
<td>60163</td>
</tr>
<tr>
<td>Travel time [hours]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Total</td>
<td>40538.56</td>
<td>15441.84</td>
<td>45534.07</td>
<td>13949.5</td>
</tr>
<tr>
<td>• Average</td>
<td>0.67</td>
<td>0.26</td>
<td>0.72</td>
<td>0.23</td>
</tr>
<tr>
<td>Travel distance [km]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Total</td>
<td>595613.7</td>
<td>595613.7</td>
<td>595613.7</td>
<td>595613.7</td>
</tr>
<tr>
<td>• Average</td>
<td>9.9</td>
<td>9.9</td>
<td>9.9</td>
<td>9.9</td>
</tr>
<tr>
<td>Delay all veh. [hours]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Total</td>
<td>33604.47</td>
<td>8243.56</td>
<td>36599.96</td>
<td>6745.55</td>
</tr>
<tr>
<td>• Average</td>
<td>0.56</td>
<td>0.14</td>
<td>0.61</td>
<td>0.11</td>
</tr>
</tbody>
</table>

As these again are not most important in describing effects of route choice behaviour the next pages contain an overview of route costs and travel time dispersion concluded by link statistics for the same selected links as before. The overviews are used in the comparison of scenarios which follow next.
Comparison 6: Scenario 2 - Scenario 6 [Influence of incident]

Scenario 2 and scenario 6 in comparison differ in the occurrence of the modelled incident. Scenario 2 is considered the reference case in this section. The driver throughout this section is considered uncertain about his mean travel time estimation. In this comparison the only difference between the two scenarios is the presence of the incident on link 7, effectively resulting in the added effect of an incident on traffic performance. No information is provided.

Route choice statistics show that in both scenarios routes South and North receive equal amounts of vehicles, which is as expected since no information is provided and traffic demand follows the same departure profile over all scenarios. Route South and North attract 77% and 23% of the vehicles respectively. Overall network performance now does not indicate better network performance in the incident scenario, which was the case when scenarios 1 and 5 were compared. This indicates that the increase in drivers choosing route South because it is perceived as the safer route combined with the incident result in severe enough queuing and spill backs to result in worse performance. Total travel time in incident scenario 6 in this case is 3000 vehicle hours higher than scenario 2.

The route cost overviews indicate that that the bandwidth in which route travel times fall are roughly the same for both scenarios. The first noticeable difference from the travel time plots is that in case of the incident route travel times increase faster from 07:00. Additionally box plot analysis on the travel times per route shows that the median travel time for route South is higher in the incident scenario. The difference however is small as it is 2650 seconds in scenario 2 and 2730 in scenario 6. Travel time dispersion through the inter quartile range (IQR) as well as the total range of travel times is slightly bigger in scenario 6. IQR is 1630 and 1740 for scenario 2 and 6 respectively. The overall travel time range is the same at roughly 4900 seconds. This indicates, despite the small differences in dispersion characteristics, higher travel time dispersion for route South in scenario 6. The conclusion is supported by the higher average travel time for route South in the incident scenario which is 3100 seconds compared to 2950 seconds in scenario 2. Route North again seems to have enough capacity to handle the traffic received in both scenarios which is supported by the small travel time dispersion and almost equal average travel time evolution. In both scenarios route North is affected by spill back. This occurs from about 08:00 in scenario 2 and 07:55 in scenario 6.
Figure 4.20 Scenario 2 on the left, scenario 6 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

Figure 4.21 Box plots for scenario 2 on the left scenario 6 on the right accompanied by box plot values.
Link analysis shows that spillback reaches link 4 earlier in case of the incident. This is as expected since the incident causes queuing to start on link 7 from 7:02. Spill back effect becomes noticeable after 45 minutes at link 4. In reference scenario 2 spill back effect is noticeable after roughly 55 minutes.

The main difference between these two scenarios is that performance measured in total travel times and delays on route South experiences an added negative effect by the incident in scenario 6. This can be concluded from both overall network statistics and link statics indicating earlier spill back on link 4 and thus substantial later emptying of the network at the end of the simulated peak period. This difference is 15 minutes between the two scenarios.
Figure 4.22 Selected link mean speeds and average travel times
Comparison 7: Scenario 2 - Scenario 3 [Influence of DRIP]

Scenario 2 and scenario 3 are different in that drivers receive travel time information in scenario 3. Other factors are kept equal and no incident is modelled. We expect to see a clear difference in travel time dispersion for route South resulting from different route choice behaviour. The difference results from drivers rerouting to the alternative route.

In scenario 2 route South and North attract 77% and 23% of the drivers respectively. In scenario 3 route South and route North attract 45% and 55% of the drivers respectively. Overall network performance shows better performance in case of information provisioning. With information provisioning total travel time is lower by roughly 25000 vehicle hours. This directly affects total vehicle delay hours and results in a lower average delay per driver, the latter being 0.14 hours compared to 0.56 hours without information and en-route route diversion. Overall network performance is thus drastically better.

The route travel time plots indicate that travel time dispersion of route South in scenario 3 has decreased. At the same time the travel time distributions of route South and North lie closer to each other than in scenario 2. Information provisioning now causes drivers to experience a maximum travel time of roughly 2500 seconds on route South which is 5200 seconds when no information is provided. The box plots show that median travel time for route South is much lower in the information scenario. The median is now at 1283 seconds as opposed to 2651 seconds in the reference scenario 2. Travel time dispersion through the IQR as well as the total range of travel times time are significantly smaller. IQR has become 625 seconds and the overall travel time range decreased to 2200 seconds.
Figure 4.23 Scenario 2 on the left, scenario 3 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

Figure 4.24 Boxplots for scenario 2 on the left scenario 3 on the right accompanied by boxplot values.
Link analysis shows that spill back does not reach link 4 anymore in scenario 3. After the first information update queuing is limited to the last non overlapping link 8 on route South. With the assumed driver informing model and route diversion this information update limits link and thus overall queuing drastically and result in lower route travel times on route South. In addition we see that the average travel times of both routes drop significantly due to information provisioning. Without information the average travel time for route South and North is 2950 seconds and 690 seconds respectively. With information the average travel time for route South and North is 1440 seconds and 660 seconds respectively.
Figure 4.25 Selected link mean speeds and average travel times
Comparison 8: Scenario 6 - Scenario 8 [Influence of DRIP]
Both scenarios include the modelling of the incident on link 7. In scenario 8 however information is provided to drivers.

Under the influence of information we see that drivers divert to route North. In total 44% of the drivers choose route South and 56% choose route North under the influence of information. This is opposed to 77% and 23% for route South and North in scenario 6. With information provisioning total travel time is lower by roughly 30000 vehicle hours. This again directly affects total vehicle delay hours and results in a lower average delay per driver, the latter decreases from 0.61 to 0.11 hours.

The route travel time plots indicate that travel time dispersion of route South in scenario 8 has significantly decreased. As a result of en-route driver route choice diversion the travel time distributions of route South and North lie closer to each other than in scenario 6. Information provisioning causes drivers to experience a maximum travel time of roughly 1000 seconds on route South. This is a clear improvement with respect to the maximum travel time of 3100 seconds in the incident scenario without information. The box plots show that median travel time for route South is lower in the information scenario. The median is now at 990 seconds as opposed to 2700 seconds in scenario 6. Travel time dispersion through the IQR as well as the total range of travel times have decreased. IQR has become 213 seconds from 1740 and the overall travel time range decreased to 1500 seconds from 4900 seconds. The observation of route cost development over time provides an indication of the number of information updates. Information is provided and updated by the DRIP on three occasions. The first update occurs after queuing starts on link 7 behind the accident and reaches link 6. As this queue continues to grow despite the diverting drivers the DRIP provides a second update as the queue increases in length and reaches link 5. This information update causes more drivers to divert and the queue behind the accident to dissolve. At about 07:30 the last update occurs when queuing is only present on link 8 and 7 and as such is contained on these two links until the end of the simulation.
Figure 4.26 Scenario 6 on the left, scenario 8 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

Figure 4.27 Box plots for scenario 6 on the left scenario 8 on the right accompanied by box plot values.

<table>
<thead>
<tr>
<th>Labels</th>
<th>Route South</th>
<th>Route North</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>368</td>
<td>399</td>
</tr>
<tr>
<td>Q1</td>
<td>2522.5</td>
<td>454.75</td>
</tr>
<tr>
<td>Median</td>
<td>2732</td>
<td>798</td>
</tr>
<tr>
<td>Q3</td>
<td>4265.25</td>
<td>871.75</td>
</tr>
<tr>
<td>Max</td>
<td>5307</td>
<td>1076.5</td>
</tr>
<tr>
<td>IQR</td>
<td>1742.75</td>
<td>417</td>
</tr>
<tr>
<td>Upper Outliers</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Lower Outliers</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mean</td>
<td>3128.494539</td>
<td>718.8882379</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Labels</th>
<th>Route South</th>
<th>Route North</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>368</td>
<td>401.5</td>
</tr>
<tr>
<td>Q1</td>
<td>887.5</td>
<td>627.5</td>
</tr>
<tr>
<td>Median</td>
<td>988.5</td>
<td>664</td>
</tr>
<tr>
<td>Q3</td>
<td>1101</td>
<td>718</td>
</tr>
<tr>
<td>Max</td>
<td>1854</td>
<td>967</td>
</tr>
<tr>
<td>IQR</td>
<td>213.5</td>
<td>90.5</td>
</tr>
<tr>
<td>Upper Outliers</td>
<td>127</td>
<td>70</td>
</tr>
<tr>
<td>Lower Outliers</td>
<td>113</td>
<td>328</td>
</tr>
<tr>
<td>Mean</td>
<td>1002.354027</td>
<td>664.4714235</td>
</tr>
</tbody>
</table>
Earlier observation indicated queuing at 07:30 to only occur on links 8 and 7, this should be represented in the link statistics for selected link 7. Indeed a decline in mean speed and average link travel time is observed from the start of the simulation. As the DRIP continues to provide information and updates the performance of link 7 increases after roughly 40 minutes in the peak period which corresponds to the containment of queuing on link 8 and link 7. As the incident is removed after 120 minutes no queuing occurs on link 7 and link performance stabilizes until the end of the simulation. We also see a temporary increase in link performance of link 7 in scenario 6 after 120 minutes. This is due to the fact that the incident is removed from the network and drivers are able to continue on both lanes. This only occurs for a few minutes as drivers join the queue on link 8 which spills back and queuing again establishes itself on link 7 until the end of the simulation.

Given the assumptions on driver behaviour in this section we see that due to DRIP information in this comparison drivers raise their expected route cost of route South above that of route North. The added effect of DRIP information with regard to comparison 4 in the previous section has a dual cause. The first cause is that route South is busier than in comparison 4, leading to increased delays. This combined with the higher updated expected route costs for route South and subsequent driver rerouting provides the explanation.
Figure 4.28 Selected link mean speeds and average travel times
Comparison 9: Scenario 3 - Scenario 8 [Influence of incident]

In this comparison both scenarios include provisioning of information. In addition to this scenario 8 also includes the modelled incident.

Under the influence of information we see that drivers divert to route South. In scenario 3 45% of the drivers choose route South and 55% choose route North. In scenario 8 44% of the drivers choose route South and 56% choose route North. As the incident in scenario 8 affects queuing on route South further evaluation sheds light on the dispersion of travel times and effect of en-route route choice behaviour on route and link performance.

The route travel time plots indicate that the development of travel time dispersion of route South in scenario 8 is more homogeneous compared to the development of dispersion in scenario 3. This observation is supported by taking into account the box plots for the two scenarios. These show that in case of the incident scenario the median is 990 seconds, which is 1280 seconds in scenario 3. Travel time dispersion through the IQR as well as the total range of travel times prove to be different as well. IQR is 625 seconds for scenario 3 and 214 seconds for scenario 8. The overall travel time range is 2200 seconds in scenario 3 and 1500 seconds in scenario 8. These travel time dispersion characteristics lead to an average travel times for route South of 1440 and 1000 seconds for scenario 3 and 8 respectively. The average travel time of route North is almost the same for both scenarios.

With regard to information provisioning queuing in scenario 3 is contained on links 8 and 7 with one information update shortly after 07:15. This is one of the main differences compared to scenario 8. Route cost development indicates that queuing in scenario 8 is also contained on links 8 and 7 but only after 3 information updates. The second information update occurs when the queue reaches link 6 and increases route cost of route South to 500 util resulting in a large share of drivers temporarily choosing route North. This happens for 15 minutes after which the end of the queue reaches link 7 and does not extend back to the up stream links for the remainder of the simulation.
Figure 4.29 Scenario 3 on the left, scenario 8 on the right with realized travel times and perceived route costs. Route North is marked pink and route South is marked blue.

Figure 4.30 Box plots for scenario 3 on the left scenario 8 on the right accompanied by box plot values.
We then see a clear drop of performance of link 7 in both scenarios. As information is provided for the first time however queuing on link 7 decreases and dissolves in scenario 3 and is limited to link 8. A sufficient amount is drivers thus updates their route cost estimation and diverts to the alternative route. In scenario 8 queuing on link 7 is not totally prevented as the accident is still present for 120 minutes while forcing a passing speed of 10 km/h. This causes the average speed on link 7 to be less than 40 km/h until the accident is removed which is 120 minutes after the start of the simulation. After the first information update the queue still extends and reaches the previous upstream link 6. This causes an additional increase in route cost of route North such that most drivers now choose route North. The rapid decrease of drivers choosing route North then allows the queue to dissolve quickly and only be present on link 8 and 7.

In conclusion the effect of the incident and resulting queuing in these two scenarios again leads to a different pattern of information provisioning. This is caused by spillback of the queue from the location of the incident. As it spills back to link 6 and 5 information is updated. This leads to temporary higher expected route cost of route South in this comparison with accompanying route choice behaviour.
Figure 4.31 Selected link mean speeds and average travel times
4.4 Discussion on simulation results

In the comparison between scenarios 7 and 7* we see less dispersion in 4 of the 6 runs in favour of drivers trusting more on travel times provided by the DRIP. In short this comparison is added to the analysis in order to illustrate the driver informing mechanism under opposite levels of driver uncertainty about own initial travel time estimation and travel times provided by the DRIP. Scenario 7 included drivers who were initially confident about their own travel time estimation. Scenario 7* included drivers who were initially unsure about their own travel time estimation. With every information update we then expect updated route costs to be higher in case of scenario 7*. In scenario 7 we see an evolution of driver expected route costs as queuing on the network evolves and information is provided starting from 229.8. The first DRIP information update raises this to 240.6, as queuing continues the second information update raises the cost again to 248.71. As queues dissolve this is also reported by the DRIP and it results in a last updated route cost for route South to 237.85.

In scenario 7* we see an evolution of driver expected route costs as queuing on the network evolves and information is provided also starting from 229.8. The first DRIP information update raises this to 243.35, as queuing continues the second information update raises the cost again to 254.09. As queues dissolve this again is also reported by the DRIP and it results in a last updated route cost for route 1 of 240.54.

The resulting effect on traffic performance and route choice statistics in turn is small however. This is due to the small absolute differences in updated route costs between the two scenarios and its resulting effect on route choice. The apparent difference in travel time dispersion can not be determined as significant since significance was not tested. Comparison of the performed runs for the scenarios indicates less travel time dispersion in case of the uncertain driver. The assumptions behind the driver informing model lead to more drivers changing route, i.e. the uncertain driver trusts DRIP travel time information more than his confident counterpart.

With respect to the research question

RQ3 What are the route choice effects of the proposed driver informing model?

the answer is that we have shown through the comparison of scenarios 7 and 7* that different levels of driver uncertainty indeed lead to different updated route costs. According to theory, a confident driver thus updates his initial anticipated travel time closer to his own estimation in light of DRIP travel time information. An unconfident driver updates his initial anticipated travel time closer to his own estimation in light of DRIP travel time information. In terms of net effect of altered route choice behaviour on network and route performance these are small but all runs indicate better performance in case of information provisioning to uncertain drivers. Since differences are small and significance was not tested this study, this study does not offer judgement on significance.

Despite our latter conclusion on non significance the performed simulation study and outcomes and discussions from earlier parts of this report, namely chapters 2 on the DRIP information market and its dynamics and chapter 3 on the driver information model, reveal some interesting relationships worth mentioning in this section.

Firstly our analysis indicates small effects of levels of driver uncertainty about travel times and route choice. This was tested through one comparison between two scenarios while only varying level of driver uncertainty about travel times and keeping other factors constant. Chapter 2 through literature reference pointed out that during driver states of unfamiliarity and unpredictability of traffic situations drivers are prone to traffic information. This finding
indicates a possible relationship between unfamiliarity, traffic unpredictability and driver uncertainty about expected travel times. Our study applies a user case based on a hypothetical driver type to capture the relationship between network unfamiliarity and driver uncertainty. This user case is then applied to all scenarios in the simulation study. The possible relationship between driver unfamiliarity and unpredictability mentioned in chapter 2 and driver uncertainty about travel times, coupled with the small effects of the latter found in this study, provides an interesting subject for further research.

The effect of information provisioning through DRIPS in this study indicates positive effects on experienced travel time dispersion and average. This is the result of drivers diverting from a route near or over capacity to a route which is not specific to the applied network in this study. This in turn not only leads to positive overall network effects but also more positive localized effects as was shown through performed link analyses. At the same time however diversion of drivers from a busy route resulted in worse travel time performance on the alternative route. The finding indicates that information provisioning might lead to better overall network performance but in turn can cause local negative effects on another part of the network. This is a consideration which road operators make in practice which was also confirmed during the visit to the Regionale Verkeerscentrale Midden-Nederland. How does this then relate to the performed driver information model and performed simulation study? Information provisioning during simulation was performed through an existing implementation of a DRIP. Underlying assumptions on DRIP functionality lead to information provisioning. One of the assumptions was the frequency of travel time updates. These updates were by default set at 5 minute intervals. In practice on could imagine a road operator wanting to adapt DRIP information provisioning due to overall network monitoring insights. One way of manipulating could be to intentionally retard provisioning of information thus influencing the amount of information provisioning. Even with a calibrated driver information model future researchers should consider this kind of tactical or strategical way of information provisioning as it possibly affects en-route driver route choice behaviour. In this particular example one needs to evaluate this kind of stakeholder behaviour in relation to modelled DRIP update frequency.

Chapter 2 also mentions the relationship between the occurrence of incidents, information provisioning and its effect on route effect. Research shows that drivers are more prone to route information and route diversion during non-recurrent traffic situations like severe incidents. During the simulation phase we found that the combination of an accident and high traffic loads lead to clear network and route performance in due to driver diversion. Although the formal relationship between the occurrence of the modelled incident and increased effect on route choice compared to regular traffic conditions was not included in this study, the implemented driver information model leaves the opportunity to further investigate and implement this relationship. We suggest investigating this relationship in terms of $\beta_{\text{VAR}}$, $\beta_{\text{I}}$ and evolution of levels of uncertainty in case of the occurrence of a incident. Effects on these parameters could result in increased importance and thus weight of mean travel time uncertainty through $\beta_{\text{VAR}}$. An increase of the weight in conjunction with increased levels of driver uncertainty leads to increased route diversion, the latter illustrated in the simulation section 4.3.5 of this study.
5 Conclusions

This concluding chapter recapitulates on the research questions mentioned in this report. The research questions are answered based on the insights and outcomes gathered throughout this study. Apart from providing the answers to the questions, the author also takes the liberty to elaborate on subjects and themes encountered throughout this thesis on a more aggregate level. Chapter 6 concludes with recommendations for further research and a reflection on the study.

The research questions:

RQ1 How can the DRIP information market be characterized and how do market dynamics affect driver route choice behaviour?

Chapter three on traffic information and the DRIP traffic information illustrated through a few different perspectives and examples that information provisioning and driver route choice behaviour is part of a complex arena. Complexity is not only created by a multitude of systems between which DRIPs as a media for travel time dissemination functions, but is also caused by the involvement of many different parties. In the DRIP information chain these systems and parties have different influences and play different roles in driver route choice behaviour.

A few examples were put forward which could affect the assumptions of the driver informing model and route choice behaviour. We see that during incident situations DRIPs are on occasion operated manually by traffic centre operators while they focus attention at the cause of an incident. In these situations operation is conducted manually which carries a high risk of retarding information provisioning via DRIPs during incidents. Considering that drivers in practise do learn from experiences facing the lack of information during these circumstances might affect driver trust in this information channel in general on the long run. In relation to the driver informing model this would result increasing the level of uncertainty of information thus leading to drivers having an updated travel time close to their own initial expectation. While the informing model in this study is not calibrated on real traffic data, a model which had been can loose explanatory power. This then leads to the necessity of recalibrating the parameters in the utility function.

Although there are just a few parties involved with maintenance of the DRIP control systems, these parties possess essential knowledge on maintenance regimes and DRIP and system defect history. Their reluctance to share this information with others can possibly negatively affect DRIP functioning as illustrated through a judicial view considering the issues which arose during the 2006 tendering procedure for maintenance of the CDMS. Such a development influences the assumptions made in a (calibrated) informing model.

RQ2 Given the lack of a driver informing mechanism in the ITS Modeller: How can driver route choice behaviour be modelled and implemented?

This report identifies an apparent opportunity for improving driver route choice modelling. The opportunity is created by the current use of a simple formal framework in explaining the use of route travel information by drivers. A driver information model is proposed in which car drivers exhibit updating behaviour on their travel time estimations and uncertainty about these times. The model fits in the current method of modelling route choice in the ITS Modeller. Our driver model is based on uncertainty about a drivers’ own mean travel time estimation and travel times provided by a DRIP. High uncertainty about his own estimation leads a car driver to update his expected travel time closer to that predicted by a DRIP. If the opposite is true then a driver updates his expected travel time closer to his initial
estimation. In other words: “Updated quality perceptions are a weighted average of prior beliefs and observed quality. Weights reflect perceived reliability of prior beliefs and observations, respectively: when the traveller distrusts (trusts) his own observations, updated perceptions of quality are relatively close to initially anticipated quality (observed quality)” (Chorus & Dellaert, Forthcoming)

RQ3 What are the route choice effects of the proposed driver informing model?

Scenarios 7 and 7* in the simulation phase illustrate the difference in driver travel time updating for different levels of uncertainty while all other factors are kept constant. The implemented driver model indeed leads to different updated route cost under influence of travel time information. In this particular comparison overall network effects due to difference in route choice behaviour were minimal though because of the small absolute difference in updated route costs. Further face validity analysis indicates that this small change in route choice behaviour early in the peak period appears to have a positive effect on travel time dispersion. This conclusion is not supported by significance and as such is made with reservation.

5.1 Elaboration on selected topics

This section elaborates on interesting relationships between different parts of this study. It is largely not based on simulation outcomes but a more qualitative analysis. In the authors opinion such an elaboration provides a valuable addition to the study in that it allows for the author to take a helicopter view on this study which also results in additional insights for further research.

Effect of compliance

During the simulation phase it became clear that the provisioning of information aids in overall network and route performance. However it was also evident that other parts of the network can experience a negative effect of information provisioning. In our case the average travel time on an alternative route dropped due to increased number of diverting drivers. In practise the compliance rate plays a role in effectiveness of provided route travel time information. In order to achieve traffic management goals road operators can try to manipulate this compliance rate? Depending on network management goals there probably is an optimum compliance rate, or at least a range within which compliance leads to desirable route choice effects and subsequent network performance. Since DRIPS mentioned in this study operate above high ways they are a governmental responsibility. Possibilities for raising awareness amongst drivers can include local advertising on radio or television. With regard to the driver information model such campaigns would aim to lower driver uncertainty about provided DRIP information in turn resulting in updated expected driver travel times to be more in accordance to DRIP travel times. One can question however how effective such awareness raising efforts will be as many drivers nowadays also have access to many other information channels whilst en-route, of which some have become quite popular like personal navigation systems. Perhaps information provisioning via DRIPS in the future should only be focussed at situations in which drivers are most prone to route and route travel time information. These are situations in which drivers are less familiar with the prevailing traffic situation or traffic performance becomes less predictable. These circumstances could include incidents, (large scale) road works and dangerous localized road conditions. At the same time awareness raising efforts could probably gain effectiveness if also focussed on these non-recurring events.
Information provisioning and calibration of driver information model

Previously we saw that there could be a relationship between manual operation of DRIPs during non-recurring traffic events. Although it is not standard practise and is limited as much as possible by road operators, manual operation of DRIPs does occur. In relation to the driver information model retardation of travel time information and other route information carries the risk of increasing the level of driver uncertainty about the information thus leading to drivers having an updated travel time closer to their own initial expectation. While the information model in this study is not calibrated on real traffic data, a model which had been can loose explanatory power. This then leads to the necessity of recalibrating the parameters in the utility function. From the visit to the traffic centre it became clear that during manual operation the traffic operator uses two tools to gather appropriate information and determine the DRIP travel time to be displayed. Using these two tools takes some time, which can amount to minutes if the operator is also busy handling an emergency event. Two interesting possibilities for further research in relation to the driver information now arise. The first is to identify the effect of this manual operation on information delay. This insight can then be applied to the modelled DRIP information update frequency or at least an alternative DRIP activation method can be modelled. The second possibility then is to investigate the effect of information delay on route choice behaviour. Future research could investigate this by for example simulator experiments with drivers receiving travel time information under varying levels of information delay. Goal of such a study would be to be able to adjust utility parameters in case of deviation from its calibrated state given delay of information provisioning. This does not only provide valuable insight to the researcher but also aids road operators to better estimate effects on route choice behaviour and network performance during non-standard DRIP operation.

5.2 Recommendations for further research

This section is structured in practical and theoretical recommendations for further research and relates to assumptions or findings through out this reports.

Theoretical recommendations:

- We recommend inclusion of truck drivers in use of the driver information model and future research. In this study a morning peak period is modelled. We assume the group of drivers only consist of car drivers (section 1.2). In practise this is not the case and this study indicated that truck drivers show different route choice behaviour in light of traffic information, specifically route and travel time information through a DRIP. The current study overestimates the effect of provided information. A first approach would be to restrict all truck drivers to set routes without route diversion in light of information. This provides somewhat of “worst case scenario”. Realistic data on truck driver route choice behaviour might be difficult to obtain, but one can imagine cooperation with a transport company in logging and analysing truck positioning data and coupling this to DRIP text logs. A private company however most likely would require some sort of incentive to join such a project.

- The utility function in our study consists of travel time and travel time uncertainty (section 3.3.1). In practise more factors may be important in a drivers’ en-route route choice consideration. Further research should investigate which factors are important. We predict that importance of factors depends on geographic location of the study area since DRIPS provide information on local network and traffic states. At the same time each geographic location can reveal different (local) driver population characteristics with regard to route choice behaviour. These characteristics may include factors like habitual route preference, maximum acceptable diversion distance and fuel cost.
Practical recommendations:

- During implementation of the model it appeared that an implementation at individual driver level would lead to too high computation times (section 3.5). We consider some opportunities for better implementation to be feasible. Firstly the ITS Modeller is used on personal working stations with limited computing power. TNO has the opportunity to use server based computation. Running the improved driver information model in such an environment might result in acceptable analysis times. An other option is further evolution of the way in which the driver information model is applied to drivers. An implementation would then be conducted analogous to current implementation of for example lane changing and car following models. Different driver classes are then defined which use the same formulation of the driver information model but with parameters unique to a specific driver class.

- We assume the lack of influence of a DRIP on network familiarity. In short route information of a DRIP does not lead to inclusion of a route in a drivers’ route set. This assumption is not so much considered a theoretical assumption as it is a modelling one. A modelled driver however should be able to consider a route even if it was not part of an initial route set. Further improvement of the driver information model ought to take this into account.

- We saw that in certain situations DRIP information delays occur outside of control of the CDMS. It is deemed beneficial if the source of this delay, manual operation, is taken into consideration and how this affects DRIP information delay. Gained insights could be used to have a future calibrated driver information model more robust.

5.3 Reflection

This section starts with a concise overview of research contributions, it then continues with a description of the research process and future improvement.

Practical contributions

- A driver information model was implemented and made available in the TNO ITS Modeller environment. As such TNO gained access to a driver model which previously was unavailable.

- The study provides insight in the practical limitation of the current model implementation. Limitations lie in computation times when actually implementing the model on the individual driver level, the current implementation causes drivers to reconsider route choice according to the DRIP update frequency which is 5 minutes. The effects this limitation has on simulation outcomes compared to the ideal situation is difficult to estimate, however for the 5 minute intervals this leads to homogenous route choice behaviour for the specific group of drivers.

Theoretical contributions

- Given the existing c-logit implementation and used network we have shed light on acceptable values for the utility coefficients and their range.

- Through an elaboration in the previous section the proposed model was placed in context and additional options for further research were identified.
**View on process**

In hindsight the process which led to this report is an interesting one, both from a personal as well as academic view. This study offered the opportunity to do research in a fairly new area of research to me, at least considering driver route choice behaviour and micro traffic simulation. At the same time I encountered difficulty in grasping some of the theoretical concepts leading to this report. More personal effort in getting a clear focus in the early stages of the study would have provided me the opportunity to get a more thorough grasp on encountered route choice modelling concepts and underlying theories. It probably also would have contributed to the overall quality of the simulation phase.

**View on product**

At times research and necessary parallel activities were not conducted efficiently enough. This especially was the case in the exploration and scoping phase. It took considerable time to apply needed focus to the study. It resulted in the project effectively taking roughly three months longer than intended. This has to be taken into account in future personal involvement in large projects.

I believe the description of the driver model implementation in chapter 3 could have been done in a more user friendly way. At the moment the inclusion of the model code is only intelligible to someone familiar with the ITS Modeller and specific java coded classes.
Bibliography


Afdeling Beheer Intelligente Transportsystemen, “Monitoring Casco (Monica), Data elementen”, Adviesdienst Verkeer en Vervoer, V&W, 2006


de Goede, M. et al., 2010. The Connected Traveller ; Factors affecting travel behaviour on an individual and network level.


Jha, M., Madanat, S., Peeta, S., (1998), Perception updating and day-to-day travel choice dynamics in traffic networks with information provision, Transportation research Part C, 6(3), 189-212

Kennisinstituut voor Mobiliteitsbeleid, 2011, Slim benutten: bereikbaarheidsmaatregelen op een rij, Ministerie I&M


Annex 1 Summary of visit to Regionale Verkeerscentrale Midden-Nederland

Utrecht, 19-06-2011
Goal of the visit: To maintain the link between route information provisioning in simulation analyses with insights from the operator of the Dutch DRIP system. This insight is used to better interpret or defend the effect of model parameters. The aim also was to get better informed about route information provisioning during incidents.

This visit was made possible by Norma Sarjoe and Henri Derks, both involved with traffic monitoring and control. Discussion was held while they were actively monitoring traffic.

First a short tour and description was given around the traffic control room, with some basic information on floor layout. The room is essentially divided in two, with regional monitoring and control located on one side and national monitoring on the other. This set up is useful to the road safety supervisors as they can quickly contact colleagues across the room in case a traffic jam or incident takes place just outside their high way monitoring area.

Then an introduction was given on tools and systems used by the traffic controllers in their goal to maintain safety and traffic throughput. The user interface of CDMS, the Dutch system which automatically controls the DRIPs, was shown and some of its features were explained. It was a rainy day and during conversation a number of incidents happened, ranging from debris on a high way lane to a car breakdown on a nose of island. This got the topic to operation of text content and strategies. During normal and recurring traffic flow patterns DRIP texts are controlled by the CDMS, for which the rules and regulations are documented in the “Richtlijn Informatievoorziening op (berm)DRIPs versie 1.0”. The same rules are also used in case of emergency, road works and a bridge opening. During these events however the controller can alter the DRIP text at specific text lines to include relevant information on for example delay cause.

In practise during incidents priority is given to clearing the cause of an incident and returning to safe traffic patterns. Only after a controller is confident that all relevant parties have been notified (road inspector, emergency services, salvage crew etc.) and urgent traffic management measures (like closing down lanes) have been undertaken possible rerouting advice is activated. In some cases this leads to a delay in information provisioning. The delay is also influenced by the method of decision making whether to reroute or not. It involves checking the CDMS graphical user interface, selecting the road section for which the controller needs an overview of average speeds, copying his selection into a decision tool complemented by other relevant information and finally getting an advise from the decision tool.

It becomes clear that this process can have a severe influence on the reliability at least in terms of timeliness of route information for drivers.

The visit ended with discussing the way in which controllers participate in improving DRIP functionality through a working group. Their practical insights are discussed in these meetings and of possible are incorporated in for instance availability of more DRIP-icons.
Annex 2 Driver information model code and project configuration file

This annex provides an overview of the implemented code in the ITS Modeller. The updating mechanism is modelled as part of the linkcostfunction java class. Code location in the linkcostfunction java class is indicated by mentioning code line numbers.

This section refers to the use of simulation statistics for the route choice model. In addition it calls user defined utility parameters which are defined in the project configuration file.

```
/* Contstructor for routechoice based on traveltime and traveltimevariance */
public LinkCostFunction(ThroughputModuleRouteChoice linkThroughputModuleRouteChoice, Network network, Double ttVariance, Double infoVariance, Double betaTT, Double betaVAR){
    this.linkThroughputModuleRouteChoice = linkThroughputModuleRouteChoice;
    this.generateFreeFlowLinkCostTable(network.getLinks());
    this.ttVariance = ttVariance;
    this.betaTT = betaTT;
    this.betaVAR = betaVAR;
    this.infoVariance = infoVariance;
}
```

This section was used to set the link variances for the route links. It can be seen that 5 non overlapping links of route have a higher variance in this model run.

```
/* Used when routes are loaded and link travel times are read from route file. Used to add travel time variance */
public double getCurrentLinkCost(Link link, double linkTravelTime, DriverType driverType){
    double linkTravelTimeVariance = Math.pow(5,2);
    // double linkTravelTimeVariance = Math.pow(7.5,2);
    if (link.getID().equals("3:12") ||
        link.getID().equals("12:13") ||
        link.getID().equals("13:14") ||
        link.getID().equals("14:15") ||
        link.getID().equals("15:16")){
        // link.getID().equals("25:24") ||
        // link.getID().equals("24:23"){
        linkTravelTimeVariance = Math.pow(6,2);
        //
        linkTravelTimeVariance = Math.pow(9,2);
    }
    double result = betaTT*linkTravelTime +
        betaVAR*linkTravelTimeVariance;
    return result;
```

This section contains the travel time and variance update equations.

```java
public double updateLinkCost (Link link, double oldLinkTravelTime, TrafficInfoMessage trafficInfoMessage){
    double result;
    double updatedLinkTravelTime;
    double updatedVariance;

    double linkTravelTimeInfo =
    translateInfoMessageToTravelTime(link, oldLinkTravelTime, trafficInfoMessage);

    double sigma1 = ttVariance;
    double sigma2 = infoVariance;
    //  double sigma2 =
    // (link.getLength()*infoVariance)/linkTravelTimeInfo;
    if (ttVariance == 0.0 || sigma2 == 0.0){
        updatedLinkTravelTime = linkTravelTimeInfo;
    }
    else{
        updatedLinkTravelTime =
        (((0.8*freeFlowTable.getLinkCost(link.getFromNode(),
            link.getToNode()))/Math.pow(sigma1,2))+(linkTravelTimeInfo/Math.pow(sigma2, 2)))/((1/Math.pow(sigma1,2))+(1/Math.pow(sigma2,2)));
    }
    if (ttVariance == 0.0 || sigma2 == 0.0){
        updatedVariance = 0.0;
    }
    else{
        //   updatedVariance = (sigma1*sigma2)/(sigma1+sigma2);
        updatedVariance =
        (Math.pow(sigma1,2)*Math.pow(sigma2,2))/(Math.pow(sigma1,2)+Math.pow(sigma2 ,2));
    }
    //variance not included
    if (ttVariance == 0.0 || sigma2 == 0.0)
        result = updatedLinkTravelTime;
    else
      //variance included
      result = betaTT*updatedLinkTravelTime + 3*updatedVariance;
    return result;
}
```

Project functionality, meaning whether or not information is provided by a DRIP and which links are to be monitored by the DRIP are activated in the RouteChoiceExample java project class. In this class a pre-run and desired simulation statistics can be activated. Parameter input is done in the RouteChoiceExample.xml project configuration file which is used by the RouteChoiceExample java project in every simulation run. The file looks as follows
<?xml version="1.0"?>
<project name="RouteChoiceExampleAangepast">
  <input file="defaultData.xml"/>
  <output path="C:\Projects\reistijdonzekerheidAangepast\9augustus\Scenario1\output1"/>
  <routeChoice On="true" perceivedVariance="true" betaTT = "0.3" betaVAR = "0.48" ttVariance = "7.5" infoVariance = "5"/>
</project>