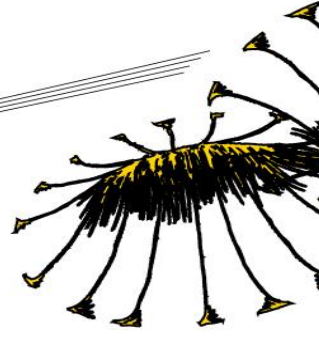# ONE ROUTE OR THE OTHER?

Development and evaluation of a day-to-day route choice model incorporating the principles of inertial behavior and quantification of the indifference band based on a real-world experiment

VirginiaTech
Transportation Institute

UNIVERSITY OF TWENTE.

M.A. (Mariska) van Essen
Master Thesis
June 24th, 2014
Final report

One route or the other?

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This document describes the research that is conducted in order to obtain a master's degree in Civil Engineering and Management with the specialization Transportation Engineering and Management at the University of Twente. The research is conducted at the Virginia Tech Transportation Institute in Blacksburg, Virginia, USA.

Master thesis
Final report

June 24th, 2014

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Preface

The report in your hands contains my master thesis about modeling behavioral mechanisms in route choice. This thesis is part of the master Civil Engineering and Management at the University of Twente. With a successful completion of this research I hope to graduate and earn a master's degree.

The psychological aspect of transportation caught in the travel behavior of (groups of) individuals has my interest for a long time. So when I initiated the graduation process I wanted to do a research related to travel behavior. In addition, I wanted to do something practical to complement the theoretical part of doing a research. I got the offer to execute an experiment about route choice and to use the obtained data to develop a route choice model based on behavioral mechanisms. This assignment was exactly what I was looking for. The only thing was that I needed to move to the United States of America for six months as the experiment was running at the Virginia Tech Transportation Institute in Blacksburg, VA, USA. So, I did…

By moving from The Netherlands to the USA, leaving my safe and well known life behind in order to experience the unknown in another culture far away from what I called home, I have not only surprised my friends and family, but also amazed myself. Pulling myself out of my comfort zone revealed capabilities I never knew I had in me and I learned a lot about myself on the personal level. It has been a once in a lifetime experience to participate in the daily life of a different culture and it has certainly enlarged my world. In addition, during the past six months of my internship at the Virginia Tech Transportation Institute I have seen and learned a lot about the academic world and how to perform an extensive experiment. Moreover, I obtained a lot of detailed knowledge about the theory on route choice mechanisms and modeling. So, all together, I can look back on a very valuable period of my life.

I would like to take this opportunity to thank all those who have contributed to this thesis. First of all, I would like to thank my supervisors from the University of Twente: Msc. Jaap Vreeswijk, Dr. Ir. Luc Wismans and Prof. Dr. Eric van Berkum. They helped crystallize the research and their time and expertise provided me with valuable insights. In addition, I am very thankful to my supervisor at the Virginia Tech Transportation institute, Prof. Dr. Hesham Rakha, for inviting me over and giving me the opportunity to do my thesis and the experiment at VTTI. His advice and suggestions during the research process were very valuable to me. I am also thankful to Dr. Ihab El-Shawarby for his guidance during the experiment and introduction process. Furthermore, I would like to thank Roeland Ottens for designing and preparing the experiment in a way that was easy to pick up and continue with, and Jinghui Wang, Arash Jahangiri, Karim Fadhloun, Andy Edwardes, John Sangster, Mohammed Elhenawy and Dalia Rakha for giving up some of their spare time to perform driving sessions, process the data, handle the cash, refuel the cars, call participants and have good times together[1]. I am also very thankful for the support of family and friends who believed in me, especially during hard times. Lastly, I've got to thank you, the reader, for taking the time to read my thesis. I hope you find it interesting and gain new insights which might be useful to you in the future.

Mariska van Essen
Blacksburg, March 26th, 2014

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[1] This experiment is not elaborated or used in the continuation of this report as it was executed simultaneously.

Summary

Background

Nowadays, traffic management is very important in daily life. Traffic management measures are developed based on extensive analyses mainly on travel behavior. The main interest of this report is route choice behavior, which is an important part of travel behavior, and route choice modeling. The most commonly used route choice theory is the utility maximization theory, which is based on the assumption that all travelers are optimizers with perfect knowledge about their choice set, presuming perfect information, rationality and homogeneity. However, there still exist some discrepancies between real-world route choice behavior and modeled route choice behavior. Therefore, the behavioral aspects of route choice have gained more and more attention in the transportation research field. Many researchers have proposed adaptations to the current modeling practice in order to include behavioral principles that are more reality alike and therewith reduce the gap between model results and in reality observed behavior. However, only a few of these studies are based on a real-world data. This gave reason for the Virginia Tech Transportation Institute to perform a large scale real-world experiment on this issue in which they asked 20 individuals to complete 20 driving sessions containing five different trips. Based on this experiment, Vreeswijk, Rakha, Van Berkum, and Van Arem (n.d.) identified four choice strategies and found that a significant number of choices concern route alternatives with the non-shortest travel time. The obtained data is used in this research to improve the understanding of route choice behavior and develop a new route choice model using the four choice strategies.

Most researches focus on route switching, while examining the behavior of individuals not changing their route choice is just as valuable. This non-switching behavior is caught in the term inertia, which represents the tendency of individuals to continue choosing their current path. As a result, this research will focus on inertial behavior and the corresponding inertia thresholds in route choice behavior.

Research objective and relevance

The objective of this research is to develop and evaluate a route choice model based on the notions of inertia and the indifference band in order to improve predictions on daily route choices of individuals and to quantify the indifference band. The focus of the research will lie on pre-trip route choices under day-to-day dynamics for the next day that a certain trip will be made. The four choice strategies as identified by Vreeswijk et al. (n.d.) will be used as a starting point.

This research is important for the transportation research field as it aims at improving route choice predictions on daily route choices of individuals and therewith reduce the gap between observed real-world behavior and modeled route choice behavior. This gap reduction makes it possible for transport operators to apply their traffic management measures more effectively. These measures might be able to push individuals towards a system optimum, which realizes a more optimal use of the transportation network but is suboptimal on the individual level. It is believed that travel information can play an important role in this. However, insights in the effect of travel information on route choice behavior are necessary. In order to obtain these insights, first, a better understanding of route choice behavior in general is needed. Insights in the inertia thresholds can

indicate to what extent individuals can be pushed into a specific direction. Besides this, research directions for further improvements in the field of route choice modeling can be identified.

Research method

In order to achieve the research objective, several steps are taken. Through a literature study the theoretical framework is shaped and the scope of the research is determined. Subsequently, the available data is analyzed. These first steps create initial feeling for the data and the principles of inertia and the indifference band. Together with a short analysis of the findings on explanatory attributes for inertial behavior and the corresponding indifference band within literature, the findings of this data-analysis is used to identify different variables that might be important in explaining inertial behavior. These variables are then used in a regression analysis in order to identify the most important explanatory variables. A regression model predicting certain choice behavior (i.e. the used choice strategy) is obtained, which is implemented within a model framework. This model is calibrated and validated using an enterwise regression method and a jack-knife cross-validation method. Subsequently, the model is extended using an agent-based approach based on Bayesian simulation in order to see the effect of this approach on the model performance. Then, the model is evaluated by executing a sensitivity analysis, followed by a comparison of the model performance to the model performance of five state-of-the-art models; the shortest path theory, the prospect theory, the regret theory, the fixed thresholds theory and the SILK-theory. Lastly, the indifference band is quantified by altering the model attribute related to travel time within the developed model. Besides this, the data-analysis and the fixed threshold theory are used to quantify the indifference band for comparison.

Results

This research resulted in a newly developed route choice model based on the principles of inertia, shown in figure 1. This 2-step-model consists of a Dynamic Expected Shortest Path Module and a Choice Strategy Module. The first module determines a preliminary choice based on a travel time updating process and the second module alters this preliminary choice based on the choice strategy predicted by the implemented regression model. An updating process for the expectation of the different route alternatives is based on a smoothing factor weighting the last experienced travel time in relation to previous experiences.
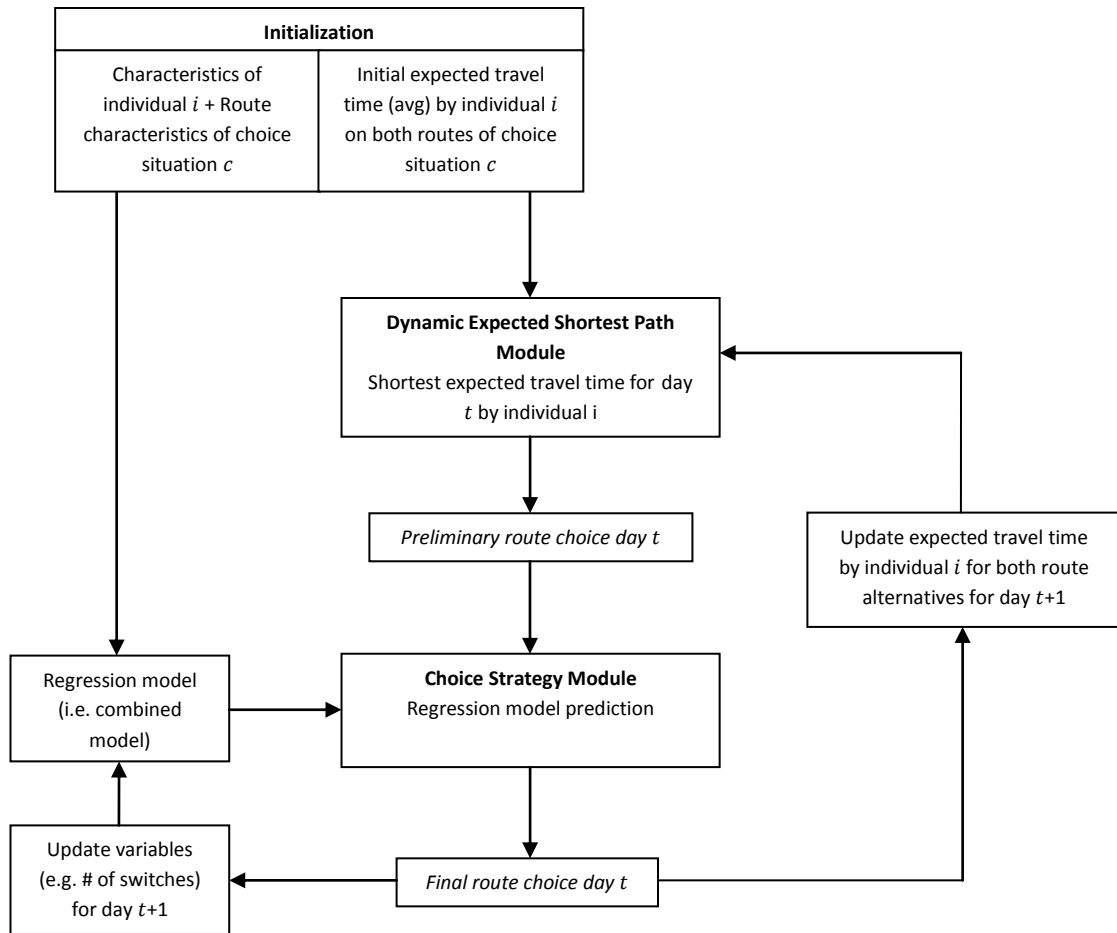
Figure 1: Developed model framework '2-step-model'

The most suitable regression model turned out to be a combined model, based on the identification of four observed choice strategies; minimizing by switching (i.e. switches to shortest route alternative), minimizing by non-switching (i.e. sticks to shortest route alternative), inertia (i.e. sticks to longer route alternative) and compromising (i.e. switches to the longer route alternative). This combined model contains two sub-models; one that is applied if at day t-1 the longer route alternative was chosen and an inertial choice strategy is possible (i.e. the inertia sub-model), and one that is applied if the shortest route alternative was chosen at day t-1 and a compromising choice strategy is possible (i.e. the compromising sub-model). According to this combined model, individual characteristics and situation-specific characteristics where found to be most important in explaining exposed choice strategies, while variables on experience were found to be less important.

The newly developed 2-step-model predicts the observed route choices of the available dataset in 75.35% of the cases correctly which places it among the highest of all state-of-the-art models. It is found that certain state-of-the-art models perform better on certain OD-pairs than others and vice versa. This indicates that in certain circumstances or choice situations a certain route choice model would be most suitable. Therefore, a hybrid model could significantly improve current modeling practice. The model performance of the prospect theory (43.17%) and the regret theory (65.88%) suggest that these choice models might not be that suitable in predicting route choices. On the contrary, the fixed threshold theory performs very well on capturing the day-to-day dynamics of route choices with 79.02% correctly predicted cases.

In order to extend the 2-step-model transforming it into an agent-based route choice model, the Bayesian modeling approach is used to simulate 1000 individuals obtaining 1000 sets of parameter representations β. When these are applied on the available dataset observations 74.55% of the cases are correctly predicted if the correlations between the model parameters are considered using the Cholesky Decomposition tool. Ignoring these parameter correlations leads to a model performance of only 51.51%. This indicates that the explanatory variables of route choice behavior are strongly correlated and are therefore crucial in obtaining accurate model results in micro-simulations.

Lastly, the indifference band is quantified using data-analysis, the fixed threshold theory and the 2-step-model. Inertia thresholds between 12.1% and 22.1% of the average trip travel time are found on an individual level. On the situational level (i.e. per OD-pair) this is 12.6% to 16.3% of the average trip travel time. Subconscious indifference bands based on perception errors (7.5%-8.7% of the average trip travel time) seem to be generally lower than conscious thresholds based on inertial behavior. These findings give an indication to what extent individuals can be pushed into a certain direction in order to realize a more optimal use of the transportation network. Data-analysis already showed that 1/3 of the observed choices contained, in terms of travel time, a suboptimal route choice. Based on this it seems that individuals do not necessarily (want to) use the optimal travel time alternative, emphasizing the potential of management measures pushing individuals into a certain suboptimal choice direction in order to establish a system optimum in the road network.

Recommendations

It is recommended to improve the current 2-step-model by further examining the effect of the travel time updating process, the determination of the initial expected travel time and how to reduce the available route alternatives to only two possible alternatives (as the current model can only be applied in the case that two choice options are available). Furthermore, it might be useful to apply the 2-step-model as well as the state-of-the-art models on other datasets in order to gain some more insights on the model performance in different choice situations. Eventually, it might be possible to determine which model would be best applicable in which situation, leading towards the development of a hybrid model. In addition, it is interesting to examine how travel time information affects the model performance of the developed model. Finally, if the model is improved and further investigation is conducted, the 2-step-model can be employed in the route choice modeling practice.

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1 Introduction

1.1 Prologue

In daily life, people want to participate in certain activities, such as work, school, shopping or family visits. These activities are usually scattered over a certain area. Therefore people need to travel from their current location to the location of the activity that is preferred for participation. These trips will be made using the road network. However, the road network can only handle a specific number of travelers at a time. In order to obtain insights in the use of the road network and to make improvements to it, transportation models are used. Based on these models, the effect of certain measures and policies can be predicted in order to increase the throughput of the road network. A commonly used traffic model that is used all over the world is the 'traditional four step model'.

The traditional four step model is developed in the 60's of the previous century. However, despite of the developments in modeling- and computer technology the structure of the model did not change. The model is based on a few travel choices a traveler has to make in order to make a trip. At first the traveler asks himself, do I need or want to make a trip? If so, he has to decide about departure time, destination, use of mode and route choice. For these four issues sub-models are used inside the traffic model. One should keep in mind that there are a lot of different sub-models available for each issue. In fact, there exist several models that account for more than one of the four issues. (Bezembinder, 2009; Immers & Stada, 2011; McNally, 2007). The main interest of this report will be the route choice models.

The most commonly used route choice theory is the rational utility maximization theory. However, there still exist some discrepancies between real-world route choice behavior and modeled route choice behavior. Therefore, behavioral aspects of route choice have gained more and more attention in the transportation research field. This research aims at improving understanding and predictions of route choice behavior by examining the possibilities to actually model some behavioral mechanisms based on empirical findings and therewith reduce the gap between real-world choice behavior and modeled choice behavior.

At the Virginia Tech Transportation Institute a large scale real-world experiment on route choice is performed by Tawfik (2012) and extended by Ottens (2013). In Tawfik's experiment travelers were asked to travel from one location to another in which they had the choice between two different routes. Some interesting route choice patterns are found, varying from travelers that do not switch routes at all to travelers that constantly change their route choice. Ottens is currently repeating this experiment except that he provided the participants with information on travel times for the available route alternatives in order to find out how their day-to-day choice behavior changes as a result of this information. The obtained data and findings of their experiments provide insights in several behavioral mechanisms on driver's route choice. In this research the data and findings of Tawfik are used. Based on the observations of his experiment, Vreeswijk et al. (n.d.) identified four choice strategies within the route choice behavior of individuals which are based on the individual's expected travel time of the different route alternatives. They found that a significant part of the choices concerned route alternatives with the non-shortest travel time. The aforementioned gave reason for the initiation of this research.

1.2 Problem definition

Modeling route choice behavior is very complex and yet essential in forecasting travelers' behavior under certain scenarios and assess their perception of certain route characteristics. These insights are used to predict future traffic conditions on transportation networks based on which policy decisions are being made. The complexity in route choice modeling emanates from the difficulties in the representation of human behavior. (Prato, 2009)

The most commonly used route choice theory in the field of transport modeling is the utility maximization theory. This theory is based on the assumption that all travelers are optimizers with perfect knowledge about their choice set. So, perfect information, rationality and homogeneity are presumed. In utility maximization the traveler determines the utilities of all routes in his choice set based on the influence of several route choice factors and chooses the route that provides him with the highest utility. The popularity of this theory exists mainly because of its mathematical clarity. (Kim, Oh, & Jayakrishnan, 2009). However, empirical studies on route choice show that travelers sometimes choose certain options that may not seem to be a logical choice. Therefore the utility maximization theory is highly criticized as being unrealistic and not representing reality alike choice behavior (Simon, 1972). Interesting theories on several behavioral mechanisms, such as bounded rationality, satisficing behavior and perception errors, are developed in order to explain these seemingly illogical choices. Understanding these behavioral mechanisms provides the possibility to model them and therewith improve the predictions on route choice.

Another necessary step towards enhancing the realism of traffic models is the understanding and forecasting of day-to-day route choices which is currently one of the most interesting and challenging areas of research within the field of transport modeling (Meneguzzer & Olivieri, 2013). After all, the travel pattern of most individuals is dominated by frequently visited locations and therewith most trips made by an individual are made on a regular basis (Schönfelder, 2006). However, individuals might use different route alternatives from day to day. As a result, one day they make a choice that seems logical, while the other day their choice might seem illogical. The commonly used route choice theories do not account for these day-to-day variations.

So, in order to further improve both traffic management and prediction reliability, it is necessary to obtain insights and understanding of the day-to-day choice behavior of individuals and develop a model that simulates this behavior more closely and realistic and therewith also accounts for the seemingly illogical choices. A lot of researchers have proposed adaptations to the current modeling practice in order to include (some of) these behavioral mechanisms, although most of them are based on (parameter) assumptions influencing the outcomes of these models. Only a few of these studies are based on a real-world experiment. In addition, most researches focus on route switching; the behavior of travelers changing their route choice. However, examining the behavior of travelers not changing their route choice, especially if this choice seems to be illogical, is just as valuable. This is caught in the term inertia, which represents the tendency of individuals to continue choosing their current path (Srinivasan & Mahmassani, 2000). Therefore, this research will focus on inertial behavior and the corresponding inertia thresholds in route choice behavior.

Using the available real-world data of Tawfik and the observed choice strategies by Vreeswijk et al. (n.d.), empirical findings on inertia can be translated into an empirical model, which is likely to obtain more accurate model outcomes than the current available theoretical models.

1.3   Research objective

The objective of this research is to develop and evaluate a route choice model based on the notions of inertia and the indifference band in order to improve predictions on daily route choices of individuals and to quantify the indifference band. The focus of the research will lie on predicting pre-trip route choices under day-to-day dynamics for the next day that a certain trip will be made. The four choice strategies as identified by Vreeswijk et al. (n.d.) will be used as a starting point.

1.4   Research questions

The objective as formulated in section 1.3 results in the following main research question:
How and to what extent can day-to-day route choice modeling be improved by incorporating the principles of inertial behavior in order to predict route choice behavior accurately and quantify the inertia related indifference band?

This research question can be broken down into three parts; (1) How to improve day-to-day route choice modeling by incorporating the principles of inertial behavior, (2) to what extent will the day-to-day route choice modeling be improved and (3) what is the value for the inertia related indifference band according to these incorporated principles of inertial behavior.

In order to achieve the research goal and answer the main research question, the following sub-questions are formulated:
Background
- What is the state-of-the-art of (daily) route choice behavior?
- Which route choice models do currently exist and how are behavioral mechanisms currently accounted for according to the literature?

'How'
- Which factors (i.e. attributes) play a role in a route choice model?
- Which modeling approach offers the best starting point to build upon and how can the behavioral mechanism of inertia be included in this approach?
- What is the effect of a disaggregated agent-based approach (i.e. accounting for heterogeneity among individuals) on the model performance?

'To what extent'
- What is the sensitivity of the model to changes and errors in attribute values?
- How does the developed route choice model perform with respect to a selection of state-of-the-art route choice models?

'Inertia related indifference band'
- How can the indifference band related to inertial behavior be quantified using to the developed model?

1.5   Research relevance

Previous sections have introduced this research. Now it is important to realize what the relevance of this research is to the transportation research field. Obviously, the objective of this research aims at improving predictions on daily route choices of individuals in order to reduce the gap between

observed route choice behavior and modeled route choice behavior. The obtained model will offer an initial starting point for this gap reduction based on actual real-world observations. In addition, in order to develop the new route choice model, individual's route choice behavior will be investigated. Together with an extensive elaboration on (the quantification of) the indifference band this research will contribute to the current understanding of the daily route choice behavior of individuals, and more particular, provide insights in and understanding of factors and mechanisms that contribute to inertial behavior. This point of view is very valuable as most of the existing knowledge of route choice behavior is obtained from route switching behavior. Therewith, the non-switching point of view associated with inertial behavior complements the current knowledge of route choice behavior. In addition, research directions for further improvements in route choice modeling might be found during the development and evaluation of the new route choice model. These might point out the important issues and subjects that can lead to significant route choice modeling improvements in the near future and therewith initiate changes for the better in the current modeling practice.

Besides these theoretical relevancies, the research importance can also be seen from a more practical point of view. In most road networks there exists a stable user equilibrium, in which each driver non-cooperatively tries to minimize his travel cost and no traveler can improve his travel time by unilaterally changing routes. These user equilibria are generally much less efficient (in terms of average travel time) than system optima in which each driver cooperatively chooses his route to ensure an optimal use of the whole system and the sum of all travel times is minimized. As rational modeling methods do not always suffice due to the suboptimal choices individuals sometimes tend to make, this might indicate that individuals can be pushed towards the, on the individual level suboptimal, system optimum.

It is believed that providing travel information can help networks to move from the user equilibrium to the system optimum. Therefore, Advanced Traveler Information Systems (i.e. any system that acquires, analyzes, and presents information in order to assist travelers) that are based on personalized distribution and sophisticated real-time learning algorithms are increasingly used as management measure. For a proper and effective application of these measures, it is important to have insights and understanding in the influence of travel information on the daily choice behavior of individuals. In identifying this influence, one needs to know first how individuals make their daily route choices without travel information. Together with the data that is currently being obtained from the extended real-world experiment containing travel time information as referred to in the prologue (section 1.1), a comparison between choice behavior with and without travel time information can be made.

The predictions of dynamic daily route choices on the individual level can be used to simulate day-to-day dynamics in traffic flows based on which, for instance, the traffic lights at several intersections can be set to operate more efficiently. It is even possible for the more advanced traffic light installations to adapt their settings based on the model predictions for the next day. This will increase the throughput in the road network and can be used to direct the network state towards a system optimum as individuals of some directions might have longer waiting times than others.

An issue that arises is that individuals need to actually accept the management measures that aim at establishing a system optimum, which may direct them towards a particular route alternative that is

disadvantageous for their own interest but improves the network performance. However, to some extent travelers may not be aware of the fact that for instance the travel information they receive is suboptimal for their situation, or they may just not be interested in it. Insights in the inertia thresholds can indicate to what extent individuals can be pushed into a specific direction in order to realize a more optimal use of the transportation network.

1.6 Research methodology

In order to answer the research questions and achieve the research goal, several steps need to be taken. These steps are visualized in a research model (see figure 2).
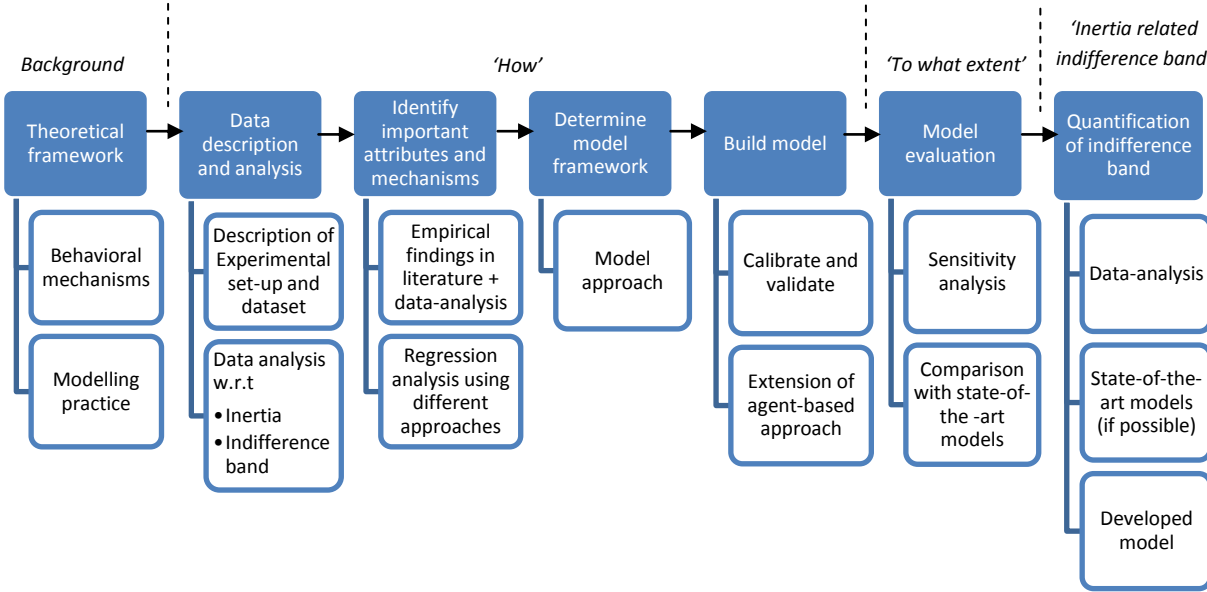
Figure 2: Research model

First a theoretical framework will be shaped for this study, which provides fundamental knowledge and background information within the scope of this research. This framework will be based on the current available literature on route choice behavior and route choice modeling and answers the first two research questions, focusing on the known behavioral mechanisms in route choice, the current modeling practices of route choice in general and of these behavioral mechanisms in particular.

Subsequently, the available dataset will be examined by getting familiarized with the experimental set-up from which the available data was originated and executing a data-analysis with respect to inertial behavior and the indifference band. Together with a short analysis of the findings on explanatory attributes for inertial behavior and the corresponding indifference band within literature, the findings of this data-analysis will be used to identify different variables that might be important in explaining inertial behavior. These variables are then used in a regression analysis in order to obtain the most important explanatory variables. Since the inertial strategy cannot be seen independently from the switching strategy different approaches will be developed based on the four different choice strategies and used in regression analyses in order to find the best way to assess inertial choice behavior.

Now the important attributes and mechanisms are identified, the modeling approach will be elaborated upon. It is preferred to keep the model approach simple and generally applicable. Within the context and objective of this research the model should focus on predicting the individual choices

of travelers on a daily base. This elaboration on the model approach will lead to a model framework, indicating how the best choice strategy regression model that was found, can be implemented within the route choice model approach.

The developed model will be calibrated and validated using an enterwise regression method and the Jack-knife cross-validation method. These are detailed methods that can be applied in a systematic manner. Subsequently, the developed model is extended using an agent-based modeling approach in order to account for heterogeneity within the population. The effect of this approach on the model performance is then assessed.

Now the new route choice model is developed, it needs to be evaluated. First, the sensitivity of the model to changes in the attribute values will be elaborated in order to obtain insights in the working of the model and the relationship between input and output variables. This is done using the most common and simple sensitivity analysis method, that is, changing one factor at a time. Subsequently, the performance of the developed model will be assessed and compared to currently existing state-of-the-art models. The model performance will be expressed in terms of correctly predicted route choices, comparing the predicted route choice for a certain data observation with the actually observed route choice. The state-of-the-art models that will be used for comparison are a selection of the choice models that are introduced in the theoretical framework. They will be selected based on the fact if they are commonly used in the field of route choice modeling and their relevancy to the subject of this research. The selected models together with the developed model will be applied on the available dataset in order to compare. Some of the models might require some calibration of their parameters, which will be done by testing different combinations of parameter values or using different values that are proposed in literature.

This research will conclude quantifying the indifference band related to inertial behavior using the developed route choice model. This is done by altering a certain attribute (i.e. related to travel time) within the model using trial and error until the route switching point within the model's route choice predictions is found. Additional approaches (i.e. the indifference band quantified based on data-analysis or state-of-the-art models) will be used in order to see if comparable values can be obtained.

1.7   Outline thesis

This is the final section of chapter 1, the introduction. The research is introduced by explaining the reasons for initiating it and elaborating on the research problem and subject. In addition, the reader is now familiar with the research objective, research questions and research methodology.

Chapter 2 will provide the reader with background information on the subject by conducting a literature study answering the first two research questions. Therewith, the 'background'-part of the research is completed.

In chapter 3 the reader will be familiarized with the available data by a short elaboration on the experimental set-up from which the available data was originated and a brief description of the data-set. Also a short analysis is performed on this dataset in order to obtain feeling for the available data in relation to the issues of interest. Chapter 4 will now identify the most important attributes to include in the model. This is followed by chapter 5 containing the development of a model

framework for the actual route choice model in which these attributes found in chapter 4 can be implemented. Now, chapter 6 will validate the improved model to justify its use for route choice predictions. Chapter 7 will then try to extend the developed model into an agent-based model in order to see the effects of this extension on the model performance. Therewith, this is the final chapter on developing the route choice model, answering the research questions on the 'How'-part of this research.

In chapter 8, a sensitivity analysis is performed on this validated route choice model in order to get a better understanding of the working of the model. This is followed by a comparison of the validated route choice model with several state-of-the-art models based on their model performances in chapter 9. These chapters together cover the 'to what extent'-part of this research.

Now, chapter 10 will quantify the inertia related indifference band using not only the newly developed route choice model, but also the findings from the data-analysis and state-of-the-art models. The indifference bands obtained by the different approaches are then compared and discussed. This chapter addresses the 'indifference band related to inertia'-part of this research.

In the last part of this report, chapter 11, this research will be finished by drawing conclusions from the findings of the covered issues and therewith provide the answers to the research questions. In addition, the research is reflected by a discussion on the research set-up and its findings and results. Besides this, side-conclusions are provided, research implications are elaborated upon and recommendations for future research are given.

2 Theoretical framework and background

In order to familiarize with the subject of this research and the corresponding research scope, this chapter will elaborate on the theoretical framework used throughout the research and backgrounds relevant to the subject. First, section 2.1 provides insights in the behavioral route choice mechanisms. Subsequently, section 2.2 introduces the general choice models that are used in route choice modeling. Section 2.3 continues with proposed choice models in the literature that focus on behavioral mechanisms. This chapter will end with some conclusions in section 2.4.

2.1 Behavioral route choice mechanisms

In general, route choice concerns the selection of routes between origins and destinations in a road network. In selecting routes, several behavioral route choice mechanisms are identified. These behavioral mechanisms are discussed in this section. Although this research focuses on the mechanisms of inertia and the indifference band, other mechanisms will also be discussed since they are closely related to each other. This way the theoretical framework will be more complete and a higher understanding about route choice behavior in general and the role of inertia and the indifference band in particular will be obtained.

2.1.1 Bounded rationality

The fundamental assumption in route choice modeling is that travelers have perfect knowledge about their choice set and are able to choose their optimal route. Simon (1972) was one of the first to criticize this assumption, since he thought it was unrealistic and does not simulate reality alike choice behavior. Opposed to this, he proposed the idea of bounded rationality in decision-making. Bounded rationality means that the rationality of individuals is limited by the available knowledge, the computational power of the brain and the finite amount of time they have to make a decision (Gigerenzer & Goldstein, 1996). These issues result in unconscious suboptimal choice behavior.

2.1.2 Satisficing

Satisficing behavior states that the individual rather seeks for a satisfactory solution that seems to be successful in achieving his goal instead of seeking for the optimal solution. So, the decision maker sticks to the first satisfactory solution he found, without continuing to search for a more optimal solution. This will minimize the mental effort in making a choice. (Gigerenzer & Goldstein, 1996)
The satisficing principle is proposed by Simon (1972) as a heuristic that succesfully deals with the limitations of bounded rationality and therefore is a good way to account for this behavioural mechanism in route choice modelling (Gigerenzer & Goldstein, 1996). However, satificing choices could be made consciously and with intent, and therefore can be perfectly rational (i.e. conscious suboptimal choice behaviour.

2.1.3 (Mis) Perceptions

A traveler bases his route choice on the sum of the influence of different route choice factors, such as travel time, traffic comfort, reliability of travel time and maximum speeds (Chen, Chang, & Tzeng, 2001). It is found that traveler's perception of these factors may not comply with reality due to for instance bounded rationality and satisficing behavior. For example, the perceived travel time on most routes differs considerably from the actual travel times (Keypoint Consultancy B.V., 2008; Vreeswijk, Thomas, van Berkum, & van Arem, 2013a); most travelers think they travel longer than they actually do. Moreover, if one factor is more important to the traveler than other factors, he will pay more attention to this factor, leading to more accurate perceptions for this particular factor

(Tawfik, 2012). So, perception errors are influenced by personal preferences. Due to these perception errors, travelers may choose the route they think is optimal for them, however, in reality it would not be the best choice for them.

2.1.4 Learning and habits

Travelers make route choices based on their individual objectives, preferences, experiences and knowledge about their journey. Previous choices they made provide them with unique experience and spatial knowledge, influencing their subsequent decisions (Zhu, Levinson, & Zhang, 2007). This means that it is assumed that drivers constantly evaluate and remember their travel times on the routes they travel and use this information for their next trip to select the route that maximizes their utility. This phenomenon is called the learning effect. Since travel patterns are for most travelers highly repetitive, trips will become familiar. This causes travelers to make travel choices in a habitual manner. For example, at one point in time, when a driver starts to travel between a certain origin and destination, he chooses his route based on a balance of the route choice factors that are most important to them. After a period of learning, drivers will use the route that provided them the most positive experience, and they will continue to use this specific route even when route characteristics change over time and the route in question might no longer be the best route for that particular driver. (Chen et al., 2001)

2.1.5 Familiarity with the road network

Familiarity can be divided in different levels; no familiarity, static familiarity, dynamic familiarity and personal familiarity. If the individual is not familiar at all, he has absolutely no knowledge about the network. Static familiarity refers to knowledge of the network structure, which includes knowledge of routes in the network, type of roads and available facilities. Dynamic familiarity refers to knowledge about traffic conditions and network performance. The highest level of familiarity is obtained through personal experience, which is a combination of static and dynamic familiarity. Familiarity with the road network of an individual might change due to external factors, such as weather conditions or time-of-day. (Lotan, 1997)

People might choose their route differently depending on their familiarity with the road network. For instance, individuals in general have better knowledge of the major roads than secondary roads or tertiary roads (Zhang, 2006a). An individual new to an area has little knowledge about the local road network, i.e. he is not familiar with the road network. However, one can imagine that unfamiliar travelers are more prone to choose routes using major roads, as they would be more familiar with those routes. The use of information might provide the traveler with a higher familiarity of the road network as the layout of the streets and their hierarchies is usually available through maps or the internet. Furthermore, learning (which is based on experience) also increases the level of familiarity as with personal experience the highest level of familiarity is achieved.

Lotan (1997) found that familiar and unfamiliar drivers exhibit different behavioral patterns of route choice. Unfamiliar drivers showed a more uniform distribution of choices, while the familiar group showed clear preferences among the alternatives. Furthermore, unfamiliar drivers switched a lot from day-to-day, while the familiar drivers showed a tendency to stick to their previous choice (i.e. inertia). In addition, Vreeswijk, Thomas, Van Berkum, and Van Arem (2013b) found that travelers who are familiar with a route perceive higher travel times on that route than less familiar travelers.

This might suggest that 'with more experiences of a particular route drivers become increasingly pessimistic or perhaps cautious' (Vreeswijk et al., 2013b).

2.1.6   Inertia

The aforementioned mechanisms of bounded rationality, satisficing behavior, habit, perception errors and familiarity can all cause an individual to stick with a suboptimal choice. Unfortunately, these different mechanisms cannot be distinguished in suboptimal choices that are observed in real world. Therefore, the term inertia is introduced. Central in the notion of inertia is the effort-accuracy trade-off. That is, exploring and testing travel options consumes time, effort and attention, which are scarce resources. Therefore, in order to simplify their decision-strategy, individuals tend to stick with an alternative that one knows to perform reasonably well, instead of trying to find the best performing option for each new trip (Chorus & Dellaert, 2010). So in short, inertia represents the tendency of users to continue choosing their current path increasing the utility of that current path (Srinivasan & Mahmassani, 2000). Note that this makes inertia a counteracting force to switching behavior.

Although inertia contains sticking to choices on both the suboptimal and optimal route alternative, in this research the focus lies on individuals sticking to suboptimal choices. This is simply because these choices are not in line with rational choice behavior and therefore it is more interesting to examine and try to model these choices. So, if in the remainder of this report the term inertia is used, it refers to sticking to suboptimal choices only.

2.1.7   Indifference band

Due to for instance bounded rationality and satisficing behavior, travelers might not recognize changes in the road network, do not have full knowledge about the available route alternatives or consider the changes to be that small that changing their route would be too much effort. Therefore, 'drivers will only alter their choice when a change in the transportation system or their trip characteristics, for example travel time, is larger than some individual situation-specific threshold' (Vreeswijk et al., 2013a). This individual situation-specific threshold is called the indifference band and might be based on travel time perception errors. For example, if there are two identical routes with equal travel times and one is being perceived as being x minutes faster, the traveler will choose this route. This driver will only switch to the other route if the travel time on the other route reduces with x minutes or the travel time of his current route increases by more than x minutes resulting in the driver being indifferent to travel time inequalities of less than these x minutes (Vreeswijk et al., 2013a). However, note that an indifference band based on travel time perception errors only defines the subconscious situation-specific thresholds of an individual which cannot be observed. In addition, there exist inertia thresholds within which the individual is aware of certain differences in route characteristics of the route alternatives, and still chooses not to switch. Therefore, these inertia thresholds are assumed to be higher than the perception thresholds. In this research, when the indifference band is mentioned, it is referred to the inertia thresholds (which, in fact, also account for the perception errors) of individuals.

2.1.8   Travel information

Travel information is very valuable for travelers as it enables the possibility to save time and, more importantly, provides certainty about the journey (Zhang & Levinson, 2008a). This certainty helps people in evaluating their route alternatives as the gained knowledge will mitigate knowledge

limitations and misperceptions. Therefore, providing information results in travelers making choices closer to their optimal choice. This can be achieved by different types of information, such as spatial information about the network connectivity and road hierarchy, information about the current traffic state (e.g. congestion) in the network or information about specific route characteristics (e.g. travel time or travel distance).

In earlier years, travel information was obtained using paper maps and listening to the radio. Due to technological developments nowadays travel information is available through, for example, navigation systems, smart phone applications and variable message signs (e.g. dynamic route information panels) along the roads. Such advanced traveler information systems may provide historical, real-time or predictive information and make it easier for the user to obtain more accurate information and therewith the user might even adjust his travel choices during his journey as he receives the information at that moment. Travel information makes the driver more aware of changes in the road network, especially gradual changes which are difficult to detect. As a result, little cognitive effort is required to identify a more optimal route alternative. Therefore, inertial behavior is likely to diminish and be replaced by optimizing behavior. Therewith route choice behavior will become more predictable.

Travel information not only reduces trip uncertainty, knowledge limitations and misperceptions, but also improves travel quality and comfort. Furthermore, it is assumed that smarter individual choices generally lead to better traffic conditions for everyone.

2.1.9 Relational framework of mechanisms

The aforementioned issues are closely related to each other (see figure 3). In short, the notions of bounded rationality and satisficing are quiet similar as the satisficing principle can be used to account for decision making under bounded rationality. An important difference, however, is that satisficing behavior can occur with rational conscious, while behavior under bounded rationality is subconscious. Both behaviors lead to misperceptions about the traffic state and road network. However, by providing travel information and the learning effect these misperceptions may be mitigated. When a traveler uses a certain route for the first time, the learning effect is the biggest. However, after a few trips the learning effect will diminish and the route choice process shifts from satisficing choice behavior to habitual choice behavior.
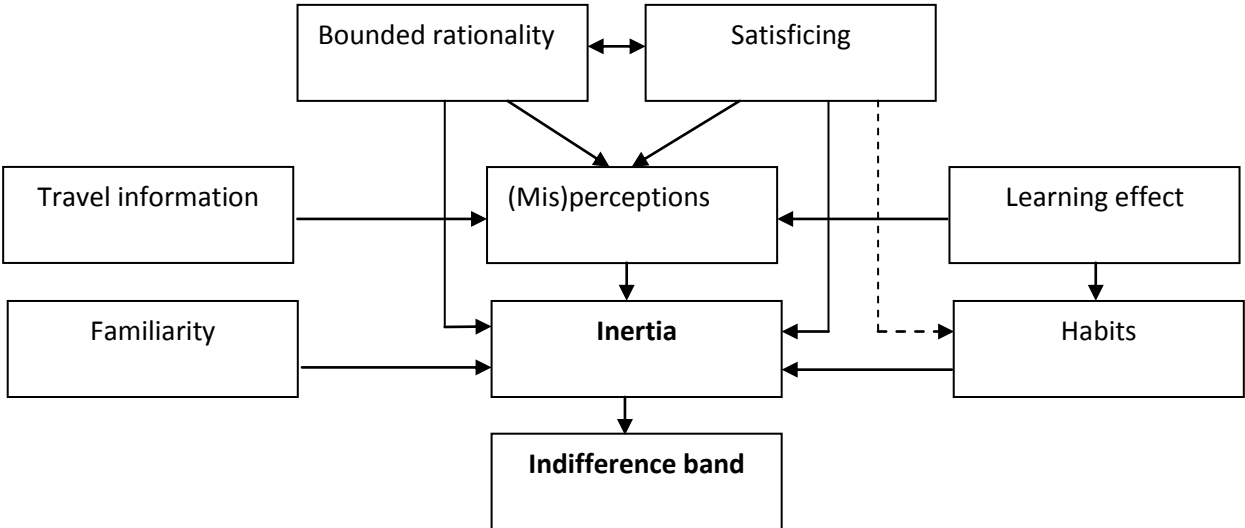
Figure 3: Relational framework of behavioural mechanisms

The effects of satisficing behavior, habitual behavior, bounded rationality, misperceptions and familiarity can eventually be observed by the inertial behavior of an individual making a suboptimal choice and sticking with this choice. This inertial behavior takes place within individual situation-specific thresholds (i.e. the indifference band), which reflects both the incapability to perceive small differences in route characteristics and the inertia of individuals to switch routes. Once a threshold is exceeded, the individual will switch his route choice.

2.2 Current available choice models

This section discusses the current available choice models; utility maximization theory, prospect theory and the regret theory. These models are founded in economics for general choice making and are well applicable to route choice situations. Subsequently, the next section will focus on choice models and methods that are specifically designed for route choice decisions and founded on the behavioral mechanisms of route choice.

2.2.1 Utility Maximization Theory

The utility maximization theory is based on the fundamental assumption that all travelers are optimizers with perfect knowledge about their choice set. Each route in the choice set receives a certain utility. This utility is based on certain attributes contributing to route choice, such as travel time, distance, reliability, etc. (Chen et al., 2001). Each route in the network performs differently on these attributes and some attributes are more important than others. The utility V for a certain route i is given by the utility function, combining the influence of all these attributes together (Ortuzar & Willumsen, 2011):

$$V_i = \sum_j \beta_j * X_{ij}$$

where X_{ij} is the value of a certain attribute j on route i and β_j is the weight of this attribute, which is assumed to be constant for all individuals, but may vary across alternatives. The sum of the different attribute values and their weights provides the utility of a certain route. A traveler determines the utilities of all routes in the choice set and chooses the route that provides him with the highest utility.

As one can notice, the utility function does not account for any behavioral mechanism and is purely mathematical. In order to incorporate more reality alike behavior several extensions are made to the standard utility maximization model, such as the random utility theory and expected utility theory.

Random utility theory
Different people can make different choices under the same circumstances. Even the same person might make different choices under the same circumstances from time to time. So, people may not always select what appears to be the best alternative, based on the attributes that are considered in the model. To capture this phenomena a random error ε is added to the utility function, which now represents the perceived utility U_{iq} of traveler q for a certain route i (Ortuzar & Willumsen, 2011):

$$U_{iq} = V_{iq} + \varepsilon_q$$

where V_{iq} is the systematic utility which is a function of the measured attributes and the random error ε_q reflects the peculiarities and particular preferences of each individual q together with attributes that are unobserved and all errors humans make during their choice making. The

stochastic nature of the error indicates the heterogeneity of human beings, i.e. no individual is alike and every person's choice behavior is different (Sikka & Hanley, 2011).

Because the introduction of a stochastic variable (i.e. the error term), it is not possible to simply determine the highest utility. Therefore, the probability of every utility to be the highest utility is used to determine the ultimate choice. To do so, the simplest and most popular practice is to assume the error term ε to be an independent and identically distributed (IID) Gumbel distribution (also called Weibull). With this assumption the choice probability of choosing route i out of a set of possible routes j by person q can be calculated using the multinomial logit model (Ortuzar & Willumsen, 2011):

$$P_{iq} = \frac{e^{\mu * V_{iq}}}{\sum_j e^{\mu * V_{jq}}}$$

where V_{iq} is the measured systematic utility and μ is a parameter that indicates the dispersion of the distribution (a high μ indicates a small distribution, a low μ indicates a uniform distribution). In this case a multinomial logit model is used as it is the simplest and most popular model. However, there exist a lot of variations, such as the nested logic, c-logit, paired combinatorial logit and mixed logit.

Expected utility theory
Although the addition of the random error term in the random utility theory corrects the basic model approach in order to obtain some more realistic results, actual human behavior mechanisms are not included. In the expected utility theory behavior is more explicitly included by considering the risk and rewards of different choices.

Making route choices is a decision process that takes place under uncertain conditions. This means that a single precise value for the different attributes considered in route choice are unknown to the decision maker. However, it is assumed that the different outcomes follow a certain distribution that is known to the traveler. So, the traveler knows the occurrence (i.e. probability) of the different situations ('states of the world') that may reveal. The expected utility of route i is then calculated by the weighted average of the utilities associated with these different situations S, where the weights are represented by the associated probabilities P. (Chorus, 2010)

$$EU_i = \sum_S (P_S * U_{Si})$$

Besides the arguably assumption that travelers correctly assign probabilities to the uncertainties in route choice, some phenomena are found which violate the expected utility theory.

Allais Paradox. In the Allais Paradox (also called the certainty effect), people have the tendency to overweight high utility low-probability cases. Allais (1953) showed that people seem to perceive a smaller difference between probabilities of 10 percent and 11 percent than between 99 percent and 100 percent. He found that people will prefer in the low-probability cases the option with the highest utility, while in the high-probability cases they will choose the most certain option, which might have a lower utility. So, people do not respond to probabilities in a linear manner as stated by the expected utility theory. (Avineri & Prashker, 2004; Tversky & Kahneman, 1992)

Ellsberg Paradox. The Ellsberg Paradox shows aversion to ambiguity. This means that if the decision maker does not know the exact values of the probabilities of some choice option, he would prefer the option in which he knows the probabilities for sure. Ellsberg (1961) showed this by letting people choose between two urns containing red and black balls from which they should pick one ball. If they picked a red ball, it means success, otherwise it means failure. However, one urn had a known ratio between red and black balls and the other urn had an unknown ratio. Overall, people preferred the option with the known ratio over the option with the unknown ratio, even if the known probability is low. (Tversky & Kahneman, 1992)

Risk seeking. There are several risk seeking choices observed. For example, the inflation of small probabilities. If in a choice set the probabilities of winning are substantial (say, 90% against 45%), most people would choose the option in which winning is the most probable. However, if the probabilities of winning are very small (say, 0.2% against 0.1%) most people would choose the option that offers the largest gain (Avineri & Prashker, 2004). Another example of risk seeking behavior occurs when people must choose between a sure loss and a substantial probability of a larger loss. (Tversky & Kahneman, 1992)

Due to these violations of the expected utility theory, researchers have tried to come up with better choice models. This resulted in the notions of prospect theory and regret theory which are elaborated in the next sections.

2.2.2   Prospect Theory

Kahneman and Tversky (1979) found that the way in which the choice options are framed could generate shifts in preferences. They identified that choice makers are risk averse towards choice options that are framed as gains and risk seeking towards choice options that are framed as losses. Together with the various violations on the expected utility theory, this finding inspired them to come up with a theory based on gains and losses; the prospect theory. This theory is based on the idea that choices are made in a two-step process, in which the initial phase consists of 'editing' and the subsequent phase covers 'evaluation'. (Avineri & Prashker, 2004; Kahneman & Tversky, 1979)

In the editing phase the choice options are organized and reformulated in order to simplify the final choice. Furthermore, the possible choice outcomes are mapped as gains or losses relative to some reference point. This reference point might be based on past experiences and expectations of the traveler in terms of travel time. Therefore, the reference point differs from one traveler to another (Avineri & Prashker, 2004). Outcomes containing travel times that are expected to be shorter than the reference travel time are perceived as gains, longer travel times as losses.

In the evaluation step the decision maker evaluates each of the edited prospects by converting the gains and losses into real values, based on weighting factors and subjective preferences. Finally the decision maker chooses the prospect with the highest value. The value for a certain route i is determined by the following formula (Kahneman & Tversky, 1979):

$$V_i = \sum_j \omega(p_j) * v(x_j)$$

where j represents the different outcomes x for route i, ω is the decision weight associated with the probability p of the jth outcome, reflecting the impact of p on the over-all value of the prospect, and $v(x_j)$ reflects the subjective value function of the deviations of outcome x_j from the reference point.

The value function is S-shaped (i.e. concave above the reference point and convex below the reference point) and steeper for losses than for gains (see figure 4). This reflects the fact that the impact of a change diminishes with the distance from the reference point and that people are considered to be loss averse (i.e. losses weigh heavier than gains) (Tversky & Kahneman, 1992).

The (probability) weighting function is shown in figure 5. The curvature represents that people overweight low probabilities, underweight high probabilities and being relatively insensitive to middle-range probabilities. This implies that decision-makers will make risk-seeking choices when offered low probability high consequence options and therewith the weighting function exhibits the characteristic pattern of risk aversion and risk seeking. (Tversky & Kahneman, 1992)
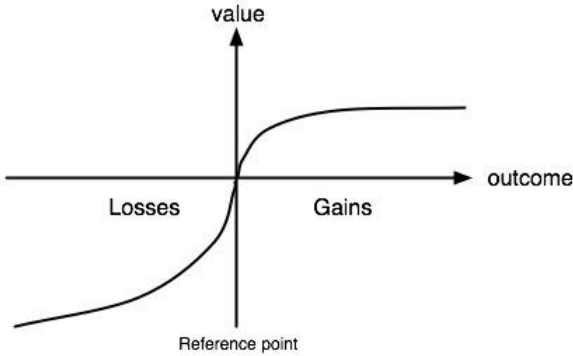
Figure 4: Value function of the prospect theory (Wikipedia, 2013).
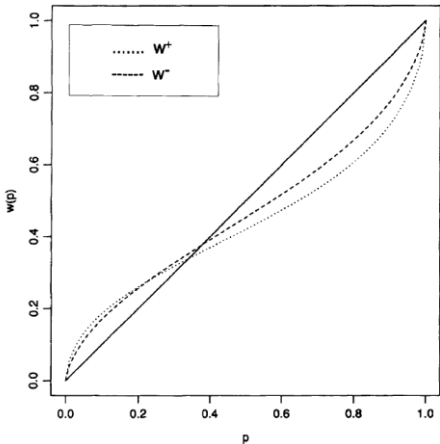
Figure 5: (Probability) Weighting function for gains (w+) and losses (w-) (Tversky & Kahneman, 1992).

2.2.3   Regret Theory

The Regret Theory is developed by Loomes and Sugden (1982). They wanted to offer a much simpler alternative theory to the Prospect Theory. The basic idea is that after making a choice, people will reflect on how much better or worse the consequence of their chosen option could be if they had chosen differently. This reflection may reduce the pleasure that derives from his current choice if the other choice turned out to be better. Conversely, knowing that he has taken the best decision provides his choice with extra pleasure, called rejoice. So, Regret Theory postulates that people will make a choice in such a way that none of the other options will outperform the chosen alternative. This means that people choose the option they are likely to regret the least. Therefore, the utility of a certain option is determined based on the performance difference with the competing alternatives.

The use of Regret Theory is not widely used in traffic modeling. However, Chorus (2012b) showed how the theory can be applied on route choice using the expected modified utility function:

$$EMU_A = \sum_s \left[p_s * \left(\frac{1 - \exp(\theta * t_s^A)}{\theta} + \left[1 - \exp\left(-\delta * \left[\frac{\exp(\theta * t_s^B) - \exp(\theta * t_s^A)}{\theta} \right] \right) \right] \right) \right]$$

$$EMU_B = \sum_s \left[p_s * \left(\frac{1 - \exp(\theta * t_s^B)}{\theta} + \left[1 - \exp\left(-\delta * \left[\frac{\exp(\theta * t_s^A) - \exp(\theta * t_s^B)}{\theta} \right] \right) \right] \right) \right]$$

where A and B represent the different routes. s again represents the different 'states of the world' (like in the Expected Utility Theory), each state being characterized by a probability of occurrence p_s, and different combinations of travel times for the two routes (t_s^A, t_s^B). θ is the risk aversion parameter and δ represents regret aversion. Higher values of θ correspond with higher levels of risk and when δ increases, regret becomes more important in making the choice. Again, it is assumed that the probabilities of occurrence of a certain state p_s are known to the traveller. Furthermore, the population of travelers is seen as being homogeneous in terms of risk aversion and regret aversion.

Note that a traveler who is risk averse and regret averse is more inclined to choose a relatively safe route than a traveler who is risk averse but not regret averse. This is due to the fact that both behavioral issues amplify each other and heavily penalize the possible occurrence of a situation where a forgone route is faster than the chosen one. So, increasing levels of regret aversion make risk averse travelers change routes towards a safer alternative. (Chorus, 2012b)

There are a few drawbacks related to the Regret Theory model. In order to obtain parameter values an extensive analysis is necessary, since parameter values for both risk aversion and regret aversion are likely to be individual- and situation-specific. Furthermore, the values of the parameters influence the route choice outcomes greatly. Therefore, it is not desired to use parameters that are obtained from empirical studies in other context or just presume parameter values. In contrary, using the prospect theory this is common practice. (Chorus, 2012b)

Another issue is that the EMU-function is only applicable for a binary choice set. In order to include multinomial route choice sets, Quiggin (1994) derived a functional form of RT based on the principle of irrelevance of statewise dominated alternatives (ISDA). This means that 'a choice from a given choice set should not be affected by adding or removing an alternative that is dominated by the other alternatives. This implies that the regret associated with a given choice alternative depends only on the actual outcome of this choice alternative and the best possible outcome that could have been attained' (Chorus, 2012b). So, in calculating EMU_A in a choice set of three available alternatives, the term $\exp(\theta * t_s^B)$ can be replaced by $Max\left[\exp(\theta * t_s^A), \exp(\theta * t_s^B), \exp(\theta * t_s^C)\right]$. However, the outcome of the RT-model when applied to larger road networks containing route overlaps is yet unclear. (Chorus, 2012b)

2.3 Proposed choice models in literature based on behavioral mechanisms

This section elaborates on proposed choice models for the behavioral mechanisms that can be found in literature as identified in section 2.1. First the SILK-theory proposed by Zhang (2006b) and the Bounded Rational Assumption Relaxing model proposed by Kim et al. (2009) are explained. Subsequently each behavioral mechanism is discussed related to the different ways of implementing that mechanism into a model.

2.3.1 SILK-theory

The SILK theory is introduced by Zhang (2006b). It concerns about how travel decisions are actually made and emphasizes on the role of Search, Information, Learning and Knowledge in travel decision-making. The assumption that travelers have perfect knowledge and are able to choose the most optimal solution is abandoned. Instead, the theory focuses on how individuals learn about the transportation system and what behavioral rules they actually use to search and choose alternatives. So, in the SILK theory, 'each individual traveler has limited and unique knowledge about the transportation system, accumulates knowledge through Bayesian learning, search alternatives using a set of search rules, make and adjust travel choices using a set of decision rules, and interact with each other' (Zhang, 2006a). This approach provides richer and more realistic representations of travel behavior. A conceptualization of the travel decision-making process in SILK is shown in figure 6.
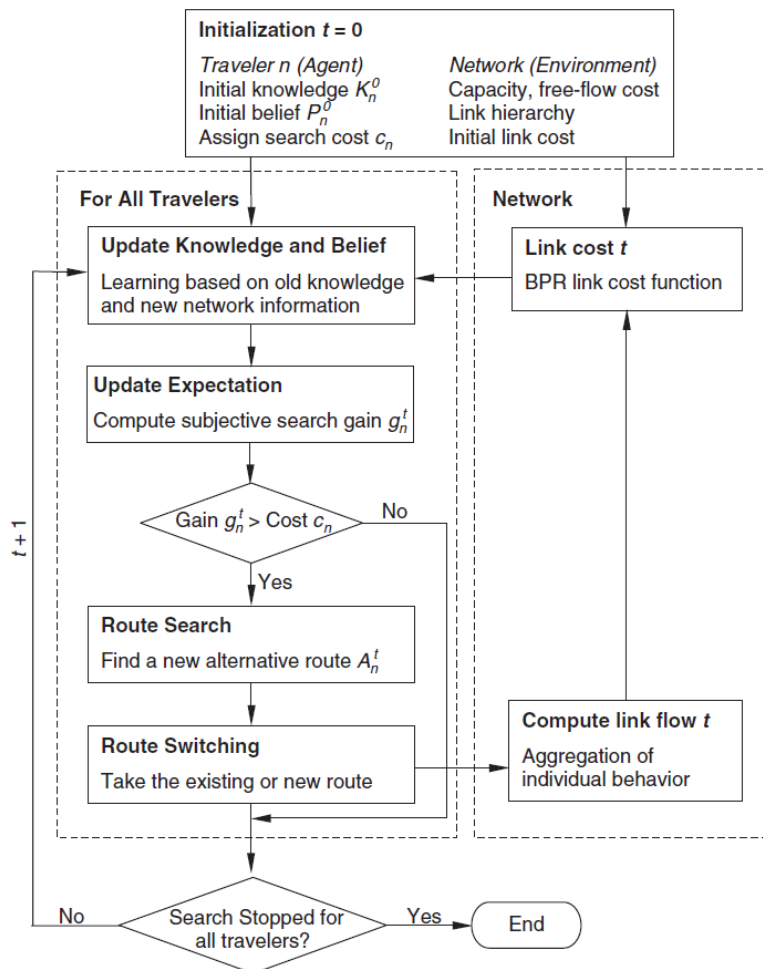
Figure 6: Conceptual framework of the travel decision-making process in SILK (Zhang, 2011).

The model based on the SILK-theory consists of two levels, the network level and the agent level. The network level is concerned with link cost as a result of the existing link flow. The agent level is concerned with the route choice of individuals. The network knowledge and subjective believes of the traveler is updated using a Bayesian learning process, which includes the past trip experiences of the traveler. Furthermore, the expectation of the traveler is updated by computing a subjective search gain, which is determined by the traveler's network knowledge and beliefs. If the subjective search cost, which is a function of the difficulty of the search task and the travelers' personal characteristic, exceeds the perceived search gain from an additional search round the traveler will stop searching for other alternatives. In that case the traveler does not believe that there exists a

better option than the currently identified alternative. During a search round the traveler uses heuristics to search for alternative routes. After a new alternative is identified, decision rules are applied to compare this alternative with the currently used and previously learned alternatives. This represents the role of historical dependency in decision-making. The route choice that is made influences the link flows on the network level and adjusts the network knowledge and subjective beliefs, due to the gained experience on the chosen route. Finally, if all travelers stopped searching for alternatives, an equilibrium state is achieved. (Zhang, 2011)

The search cost that an individual perceives is assumed to be constant throughout the search process and need to be empirically derived. The subjective expected search gain of an individual from an additional search can be calculated in terms of travel time savings per trip (Zhang, 2011):

$$g = \frac{t_{min} - t^*}{N + 1} \qquad t^* \leq t_{min}, \qquad g > 0$$

Where t^* is the free flow travel time of the route identified during the first search round, t_{min} is the minimum of all observed travel times of the searched routes and N is the number of searches.

Heuristics for finding route alternatives and route choice are developed based on empirical data. The rules for finding route alternatives suggest that drivers will only identify a specific route in a round of search if its travel time is significantly lower than the travel time of other routes. As the travel time difference becomes smaller, other factors related to the simplicity of routes play a more and more important role. The rules for route choice represent some kind of indifference band together with certain attributes such as familiarity, pleasure, commute time, delay, number of stops and income. The heuristics as identified by Zhang (2006b) are shown in appendix A.

2.3.2   Bounded rationality – Relaxing assumption model

The notion of bounded rationality conflicts with the fundamental assumption of route choice modeling that states that travelers have perfect knowledge about their choice set and that they will choose the most optimal solution (i.e. are optimizers and thus rational).
Kim et al. (2009) tried to model bounded rationality by relaxing this assumption. The assumption of perfect information is relaxed by modeling the drivers' perceived travel time that is updated through their experience (i.e. learning). So, their information source only exists of their previous experiences. The assumption of rational behavior is relaxed by incorporating a preference update process in the (inductive) learning process, which can be seen as some kind of indifference band. This preference is modeled by considering the travel time difference between expected and experienced travel time. They have incorporated these adjustments into a general model framework (see figure 7).
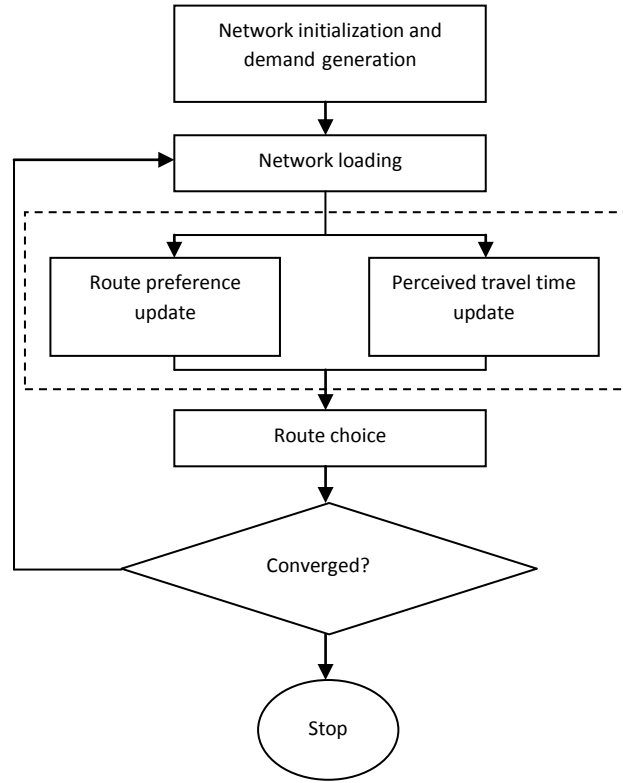
Figure 7: General model framework by Kim et al. (2009).

Perceived travel time update

In this part of the model framework, drivers update their expected link travel times based on their previous experience. This is implemented using a recursive equation which employs a simple weighted average, implicitly assuming a limitation in the driver's memory. (Kim et al., 2009)

The driver's initially expected link travel times are determined by his perception on the level of network congestion and a random perception error on each link (Kim et al., 2009):

$$\bar{t}_{m,i}^0 = \alpha_m * \left(t_i^f \pm \beta_{m,i} * t_i^f \right)$$

(1)

where $\bar{t}_{m,i}^0$ represents the initial expected travel time of link i by driver m, t_i^f is the free-flow travel time of link i, α_m is a parameter for driver m's perceived congestion level and $\beta_{m,i}$ is a parameter for driver m's random perception error on the free-flow travel time of link i. The parameter α_m is regarded as the level of information. (Kim et al., 2009)

The expected travel time for the next day is then expressed as (Kim et al., 2009):

$$\bar{t}_{m,i}^{d+1} = (1 - s)\bar{t}_{m,i}^d + s * t_{m,i}^d$$

(2)

where $\bar{t}_{m,i}^d$ represents the expected travel time on link i on day d by driver m, $t_{m,i}^d$ stands for the experienced travel time on link i on day d by driver m. s represents a learning rate, scaled from 0 to 1. The expected travel times are updated only on the links that driver m used on day $d - 1$. This link-based approach allows to partial update for the unused routes that share some links with the used route.

After updating link travel times, the expected route travel time is computed by summing travel times on links that are part of the route (Kim et al., 2009):

$$\bar{T}_{m,p}^d = \sum_i \delta_{m,p,i} * \bar{t}_{m,i}^d$$

(3)

where $\bar{T}_{m,p}^d$ is the expected travel time on route p on day d by driver m and $\delta_{m,p,i}$ is an incidence indicator which is valued 1 if link i is part of route p, otherwise its value is zero.

Route preference update

Route preference is modeled as a process of evaluation and update. Drivers evaluate their route choice decision by comparing their experienced travel time with their expectation. If their experienced travel time on one route is shorter than expected, their preference on that route will increase and vice versa. This way a route preference map is build for each driver. The process of route preference updating is expresses as (Kim et al., 2009):

$$\varphi_{m,p}^{d+1} = \varphi_{m,p}^d + \gamma\left(T_{m,p}^d, \bar{T}_{m,p}^d\right)$$

(4)

where $\varphi_{m,p}^d$ represents driver m's preference for route p on day d, $T_{m,p}^d$ is the experienced travel time on route p on day d by driver m, $\bar{T}_{m,p}^d$ stands for the expected travel time on route p on day d by driver m and $\gamma(\dots)$ represents a route preference function based on the difference between expected and experienced travel times. The γ-function is defined as follows (Kim et al., 2009):

$$\gamma\left(T_{m,p}^d, \bar{T}_{m,p}^d\right) = \begin{cases} 0 & if \left|\dfrac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d}\right| \le \varepsilon \\ \sigma_m * \left(\varepsilon - \dfrac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d}\right) & if \dfrac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d} > \varepsilon \\ -\sigma_m * \left(\varepsilon + \dfrac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d}\right) & if \dfrac{\bar{T}_{m,p}^d - T_{m,p}^d}{T_{m,p}^d} < -\varepsilon \end{cases}$$

(5)

where σ_m is a sensitivity parameter for change in preference and ε is an indifference band on preference. A value of the route preference function below 0 represents a gain in preference for the current route, while a value above 0 means that an individual loses preference on that route (Kim et al., 2009).

Route choice decision

The route choice decision is now made based on the following (Kim et al., 2009):

$$p_m^d = \arg\min_{\mathrm{p}}(\varphi_{m,p}^d * \bar{T}_{m,p}^d)$$

(6)

2.3.3 Bounded rationality and satisficing behavior

As proposed by Simon (1972) the principle of satisficing behavior is a good way to simulate the mechanism of bounded rationality. Satisficing behavior is mostly modeled by certain decision rules and heuristics (Mahmassani & Chang, 1987; Zhang, 2011). The SILK-theory that is introduced in section 2.3.1 provides a good example of this.

Another example is the satisficing rule that is provided by Mahmassani and Chang (1987) in order to model departure time. Their satisficing decision model assumes that each commuter i has an indifference band (bounded by IB_{it}^- and IB_{it}^+) of schedule delay SD_{it} on day t, such that he will maintain the same departure time as long as the previous arrival time is within this indifference band:

$$if\ IB_{it}^- \leq SD_{it} \leq 0 \qquad or \qquad 0 \leq SD_{it} \leq IB_{it}^+$$
$$Then\ accept\ DT_{i,t}\ and\ set\ \ DT_{i,t+1} = DT_{i,t}$$
$$Otherwise\ DT_{i,t+1} \neq DT_{i,t}$$

Furthermore, Yi and Sarin (2013) are working on a dynamic model of satisficing behavior. They introduce the principle in which the decision maker has some kind of satisficing level and expects some pay-off from an option. If the perceived pay-off of an option turns out to be above the satisficing level, the option is continued and the expectations of that option are updated. However, if the pay-off and expectations are below the satisficing level, both the satisficing level and the expectation of the chosen strategy are updated and another option is chosen.

Besides satisficing, bounded rationality can also be modeled otherwise. For example, by relaxing the fundamental assumption of an all-knowing traveler with rational behavior. The relaxing assumption model of Kim et al. (2009) realizes this by including the learning aspect and a preference update process. The SILK –theory even abandons the fundamental assumption and uses the perspective of updated experience, learning and (spatial) knowledge in order to approach the route choice decision making from a more behavioral point of view and therewith incorporating the notion of bounded rationality.

Furthermore, Guo and Liu (2011) developed a day-to-day model that accounts for bounded rationality. They state that 'the travel cost of any used path can be higher than the shortest path, but within a certain threshold' (Guo & Liu, 2011). Subsequently they define an acceptable path set under given cost with the accompanying acceptable path flow set and acceptable link flow set. Their model can be mathematically represented by solving the following problem:

$$Minimize\ D(x, y)$$
$$Subject\ to:$$
$$y \in \Omega_x^{br}\big(c(x)\big)$$

where the constraint $y \in \Omega_x^{br}\big(c(x)\big)$ means that y is an acceptable flow under the current cost $\big(c(x)\big)$ and $D(x, y)$ is a measure of the distance between the target flow y and the current flow x. Guo and Liu (2011) suggest that $D(x, y)$ can be represented, for example, by the Euclidean distance $D(x, y) = (x - y)'(x - y)$ or by a formulation proposed by He, Guo, and Liu (2010), $D(x, y) = \sum_{a \in L} \int_{x_a}^{y_a}\big(c_a(w) - c_a(x_a)\big)dw$. So, in other words, the target flow y is the acceptable flow under the current cost $c(x)$ that is closest to the current flow x. The boundedly rational day-to-day dynamic model consists of the following steps:
- Step 1. Initiate day t with link flow x^t. Determine link cost $c(x^t)$ and path cost $F = A'\ c(x)$.
- Step 2. Generate the acceptable link-path incidence matrix (i.e. exclude unacceptable paths)
- Step 3. Solve minimization problem $D(x, y)$ to obtain target flow y^t
- Step 4. Update link flow to get link flow x^{t+1} on day $t + 1$.

Updating is done using the following formulas:

$$x^{t+1} - x^t = \alpha(y^t - x^t)$$
$$y^t = argmin\, D(x^t, y^t)$$

where α is a step-size parameter ($0 < \alpha \leq 1$).

2.3.4 Learning

In order to model the effects of learning and habits a day-to-day dynamic model is necessary to account for the historical dependency of these behavioral mechanisms. The SILK model and assumption relaxing model are both examples of such a model, including a learning aspect based on past trip experience.

Nakayama and Kitamura (2000) developed a route choice model using inductive learning based on memory content and if-then rules (figure 8). The memory content contains the travel time experience of 1 to m days ago. It is assumed that travel times are stored in the traveler's memory in an approximate manner. Therefore they have divided the range of travel times into several intervals. For each experience, there exists an if-then rule consisting of a condition and an action. The action prescribes the route that will be chosen. The condition exists of a set of x_{ijk} (valued 0 or 1), where i refers to the route, j to the day of travel and k to the travel time interval. If a rule matches the memory the rule is activated by the processor. It might be the case that more than one rule matches the memory. In order to decide which rule should be applied, an inferiority indicator is used. This indicator is a weighted average of the travel times experienced on the route that is chosen according to the rule. An example of an if-then rule is provided in figure 9.
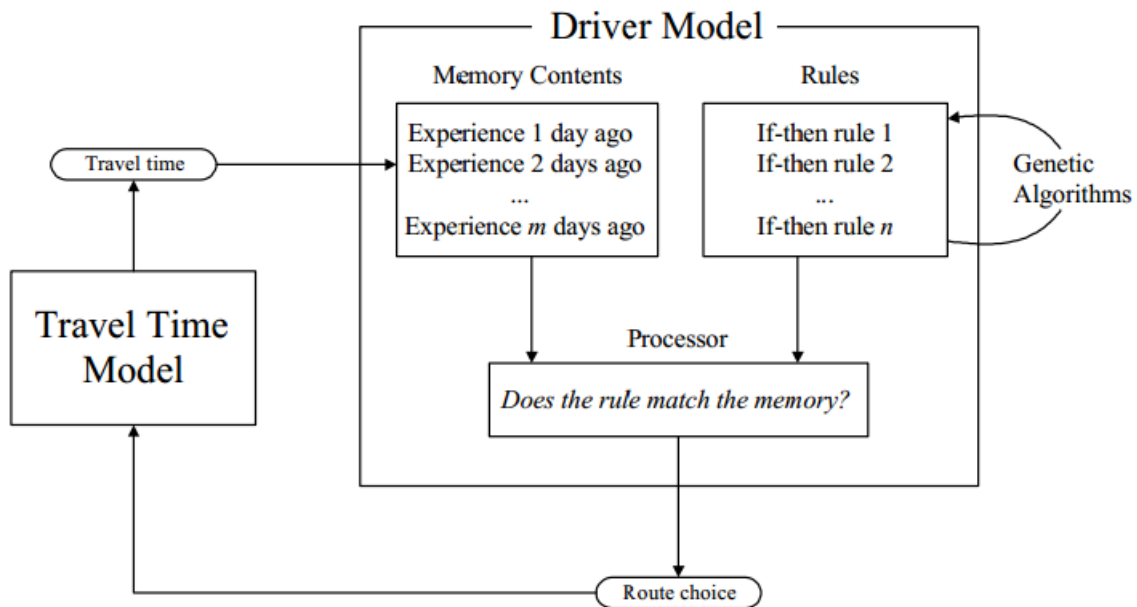
Figure 8: The inductive learning model of Nakayama and Kitamura (2000)

Figure 9: Example of an if-then rule (Nakayama & Kitamura, 2000)

The learning mechanism is then simulated by updating the set of if-then rules of a traveler using genetic algorithms. Genetic algorithms exist of three parts; reproduction, crossover and mutation. In the reproduction part, a certain number of rules with the highest inferiority value are deleted, while the rules with the lowest inferiority values are propagated. Subsequently, in the crossover part, the remaining rules are paired and random x_{ijk}'s from these pairs are combined to create new rules. This is followed by the mutation part in which an occasional (i.e. with a small probability) random alteration of the values of the x_{ijk}'s of each new rule. (Nakayama & Kitamura, 2000)

2.3.5 Habits

Kim et al. (2009) introduced a sensitivity parameter to account for heterogeneity in drivers' preference and found that drivers with a high sensitivity might develop strong habitual route choice behavior. Therefore it is suggested that habit can be modeled by including different levels of personal preferences. Furthermore, habit can modeled as being an attribute in the utility function as is done by Vaughn, Kitamura, and Jovanis (1996) and Bogers, Viti, and Hoogendoorn (2005). The last specified habit as the variable 'number of times the person had already chosen that route in the past'.

Furthermore, van der Mede and van Berkum (1993) came up with a choice process in which the traveler chooses a route based on the expected utility maximization theory or chooses according to habit. This is summarized by:

$$P_{irt} = H_{it} * PIN_{irt} + (1 - H_{it}) * PUM_{irt}$$

where P_{irt} represents the probability that individual i will choose rout r at day t, H_{it} is the habit strength, PIN_{irt} is the probability that route r is chosen out of habit and PUM_{irt} denotes the probability that route r is chosen out of utility maximization.

The total strength of habit for individual i at time t is:

$$H_{it} = H_{it} * \sum_{r \in \wedge D_{it}} PIN_{irt}$$

The amount of habit changes when a route was chosen and the experience was good. Therefore, the probability of a habitual choice is defined as:

$$PIN_{irt} = \frac{\gamma PIN_{ir,t-1} + \delta_{ir,t-1}\sigma_{i,t-1}}{\gamma + \sum_{p \in \wedge D_{it}} \delta_{ir,t-1}\sigma_{i,t-1}}$$

where σ_{it} is '1' if the difference between the experienced travel time and the expected travel time is smaller than some threshold (i.e. the route chosen yields a good experience), otherwise the value is '0'. Furthermore, δ_{irt} is '1' when route r was chosen and '0' otherwise. The parameter γ determines the speed with which the distribution of habit is built up as a result of that specific choice.

2.3.6 Perception

The assumption relaxing model provides a formula to determine the perception of link travel times based on the driver's perception on the level of network congestion (see section 2.3.2). Besides this, a random perception error is included on each link. The random utility theory (section 2.2.1) also includes an error term in which, among others, is accounted for misperceptions. This way of accounting for perceptions in choice models is vastly used in literature.

Furthermore, Tawfik (2012) has developed a perception model that incorporates more than just adding an error term in order to model the perception of travel distance, travel time and travel speed. He used a multinomial distribution structure:

$$y_{ic} \sim Multin(p_{ic1}, p_{ic2}, p_{ic3,})$$
$$p_{icm} = \Phi(\zeta_m - (x'_{ic}\beta + \theta_i)) - \Phi(\zeta_{m-1} - (x'_{ic}\beta + \theta_i))$$
$$\theta_i \sim N(0, \varphi)$$

where y_{ic} represents the perception of person i at choice situation c (i.e. response level or model outcome; 1: correct perception, 0: no difference, -1: opposite perception). p_{icm} is the probability that person i's perception at choice situation c will be of level m, which is the response level (i.e. -1: opposite perception, 0: no difference, 1: correct perception). Φ is the cumulative Normal distribution function, ζ_m is the break point for response level m ($-\infty = \zeta_0 < \zeta_1 = 0 < \zeta_2 < \zeta_3 = \infty$). x_{ic} is the vector of covariates for person i at choice situation c, β is a vector of the parameters, θ_i is the random component of person i, N is the Normal distribution and φ is the variance. The independent variables that are included are related to driver demographics, driver personality traits, driver experience and familiarity with the road network.

2.3.7 Indifference band

Carrion and Levinson (2012) developed a choice model based on travel time indifference bands as they found that travelers react to day-to-day travel times on a specific route according to thresholds. The idea is that the traveler determines a travel time threshold and therewith creates an acceptable time margin. The travel times of the trips made by the traveler are assessed related to this acceptable time margin. Depending on the frequency that the experienced travel times on a certain route lie within the acceptable time margin the traveler might decide to switch to another route alternative. Based on this principle, Carrion and Levinson (2012) presented two models of

indifference bands; the fixed threshold model and the moving threshold model (see figure 10). In the fixed threshold model it is assumed that individuals have a strict expectation about their travel times and travel time variability. The moving threshold model, however, assumes that individuals continuously update their margins based on the experienced travel times in previous trips. Both models assume a moving set of travel times, referring to the travel times of past trips that the individuals have remembered (2 to 15 days before the specific day of travel of a trip). Trips above the thresholds are referred to as late trips and trips below the threshold as early trips. Trips within the thresholds are regular trips. The individuals are more likely to leave the current route if the number of late trips increases, and more likely to stick with their current route if the number of early trips increases.
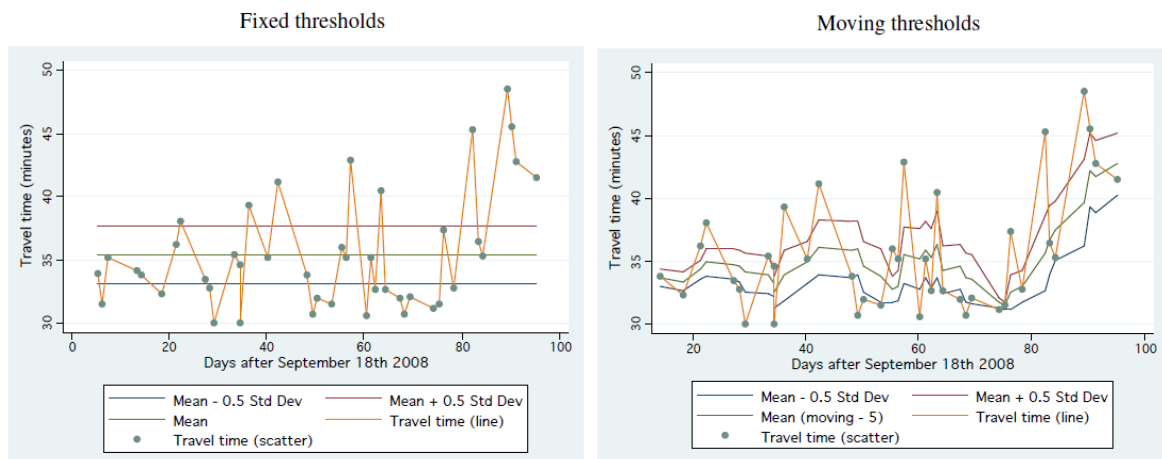
Figure 10: Fixed threshold model versus Moving threshold model (Carrion & Levinson, 2012)

Mahmassani and Liu (1999) expressed the indifference band of user i at decision node j on day t for pre-trip route selection and en-route path switching as follows:

$$IB_{ijt} = \max\left[\eta_{ijt} TTC_{ijt}, \pi_{ijt}\right]$$

where η_{ijt} represents the relative indifference band as a fraction of the TTC_{ijt}, which is the trip time of the current path, from the decision node j to the destination of user i on day t. π_{ijt} represents the corresponding minimum trip time saving from decision node j to the destination that is necessary for user i to switch from the current path on day t. They composed their relative indifference band η_{ijt} of an initial band together with components accounting for user characteristics, information reliability, schedule delay and unobserved issues.

2.3.8   Travel information

Most research about the influence of information on route choice make use of the (random) utility maximization theory in which information provision or information related phenomena are among the used attributes (e.g. (Shiftan, Bekhor, & Albert, 2011; Zhang & Levinson, 2008b)). These researches indicate significant influence of information on route choice.

Srinivasan and Mahmassani (2000) found two phenomena related to route choice in the presence of real-time information; inertia and compliance. Inertia represents the propensity to remain on the current path, while compliance indicates the tendency to choose the path that is recommended by the en-route traffic information system. These mechanisms are incorporated in the utility functions of the route alternatives. Their findings strongly support the presence of both mechanisms in route

choice behavior. They also found that the driver's past experience with traffic information, network conditions and information quality influence the mechanisms of inertia and compliance.

Zhang and Levinson (2008a) found that the value of information for the traveler depends on a number of factors. They developed an utility function for the utility of driving with or without traveler information based on those factors; the accuracy of information, the attitude of the traveler towards traveler information (i.e. the perceived usefulness), the familiarity with the route alternatives, the level of congestion in the road network, the perceived information acquisition and processing cost and the travel patterns of the drivers (e.g. commute time, travel distance, trip frequency). Furthermore, they found that the importance of information provision was the highest for trips with a commuter or event purpose, which can be explained by the experienced time pressure in order to arrive at the destination on time.

Ben-Akiva, de Palma, and Kaysi (1991) integrated information provision on route choice by updating the estimated travel time on a route based on a weighted average of historical perception and travel time information. The updated estimation is given by Jha, Madanat, and Peeta (1998):

$$I_u = \alpha * I_h + (1 - \alpha)I_i \qquad 0 \leq \alpha \leq 1$$

where I_h is the historical perception and I_i is the travel time that is provided by ATIS. α indicates the relative importance of information and historical perception in the updating process. Ben-Akiva et al. (1991) included this updating process in their dynamic modeling framework.

2.3.9 Familiarity of road network

As with information, in most research familiarity is included as an attribute of a utility function (e.g. Lotan (1997)). Furthermore, familiarity has a lot in common with the knowledge and experience of drivers and therewith is closely related to learning. Therefore, the SILK theory and assumption-relaxing-theory and the inductive learning model of Nakayama and Kitamura (2000) implicitly account for familiarity. Models specifically focusing on network familiarity are not found.

2.3.10 Inertia

Several studies model the diversion decision from a given current path instead of actual choices. In these models the principles of inertia are captured through an alternative-specific constant that is confounded with the baseline levels of other categorical variables in the models. However, this way of modeling is not very behaviorally robust (Srinivasan & Mahmassani, 2000). Therefore, Srinivasan and Mahmassani (2000) included inertia as a separate attribute in a utility function. Bonsall (1992) did something similar by introducing the following route switching rules:

Stay on strategical current route s, unless new information i indicates that C_s or C_p is significantly different from the costs on which the strategic current route choice was based.
Change route if: $C_p + \Delta_p < C_s + \Delta_s - \alpha_{di}$

where C_p and C_s are perceived costs to reach the destination via the potential new route and the strategic current route, respectively. Δ_p and Δ_s are the perceived changes (both positive and negative) to these perceived costs and α_{di} represents inertia in favor of staying on the strategic current route for driver d in respect of new information from source i.

Lastly, Peeta and Yu (2005) developed a hybrid model for driver route choice in which they come up with fuzzy if-then rules for among others inertia. The attributes they used for inertial behavior are weather conditions, time-of-day and trip purpose. It needs to be mentioned that these attributes are just chosen on common sense. No research was used to come up with these attributes. Furthermore, they developed a multinomial logit model to benchmark their hybrid model performance. In this model, inertia is included as a dummy variable being one if route i is the current route and zero otherwise.

Although inertia is theoretically included in several model approaches, models predicting inertial behavior itself are not found.

2.4 Conclusion

This chapter provides a theoretical framework for this research by answering the first two research questions. Knowledge about behavioral mechanisms in route choice (i.e. state-of-the-art of route choice behavior) is gained. In short, it is found that there are several behavioral mechanisms causing individuals to make irrational route choices. Although these cannot be observed, they lead to certain observable behavior, that is, sticking to a suboptimal route alternative. This is defined as inertial behavior. In addition, knowledge about the current choice modeling practice in general together with a more specific modeling practice based on behavioral mechanisms is gained. Three general choice models are identified, all having their own limitations and criticisms. Several models specifically focusing on capturing (some of the) behavioral mechanisms in route choice are found within literature, supplemented by approaches to represent a single behavioral mechanism instead of coming up with a full working model. The gained knowledge about these backgrounds can be used in order to design a route choice model and find important issues that should be accounted for.

Note that this theoretical framework provides insights and understanding about the topic of interest, research scope and definitions for both the researcher and reader. It is important to remember that in the remainder of this report inertia refers to the behavior of individuals sticking to a suboptimal choice and that the indifference band indicates the corresponding inertia thresholds.

3   Data description and analysis

Now the research subject is introduced and the theoretical background is elaborated, the next step is to explore and analyze the available data. This chapter will first introduce the experimental set-up that is used to obtain the data (section 3.1). Subsequently, section 3.2 discusses the dataset, followed by a short analysis of the data with respect to inertial behavior and the indifference band in section 3.3.

3.1   Experimental set-up

The data that is used in this research is collected by Tawfik. He collected data through a real-world route choice experiment which took place in Blacksburg, Virginia, USA. A total of 20 participants were involved in this study. They were asked to complete 20 experimental runs over 20 days during peak hours on regular school week days in 2011 using specially equipped research vehicles. There were three peak hours; morning (7-8 am), noon (12-1 pm) and evening (5-6 pm) and all runs for a driver i were done at the same time each day. Participants were provided with five Google Maps print outs (see figure 11), each presenting one trip with one point of origin p, one point of destination q and two alternative routes. For each experimental run, participants had to make these five trips assuming that the provided route alternatives were the only available routes between that particular origin p and destination q. The OD-pairs and the route alternatives were selected in such a way that the five choice situations c would differ from each other. All driver choices as well as the experienced travel conditions were recorded through a GPS device located in the research vehicles and a research escort in the back seat. The participants were instructed to behave as if they would in real life. To ensure that participants will not consider the experiment as leisure, their compensation was not a function of the time spent in the experiment; they just received a flat monetary amount per run. Furthermore, the experiment was not entertaining as the participants were not allowed to listen to entertainment, use their cell phone or chat with the research escort. Besides, the provided route alternatives were not scenic.
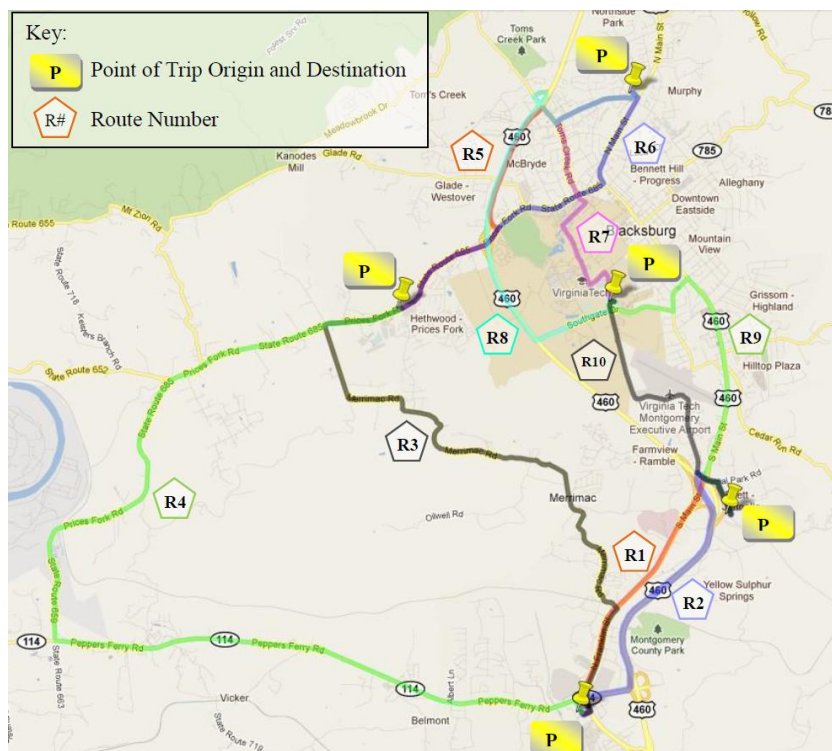
Figure 11: Print out with available routes between the five OD-pairs.

In addition to the driving sessions, the participants were asked to complete a pre- and post-task questionnaire. The pre-task questionnaire collected information about the participants' demographics and driving experience, the post-task questionnaire collected information about the participants' perceptions of the traffic conditions on the alternative routes and preference levels of these routes. Besides this, they had to fill in a Personality Inventory; the NEO-FFI-3. This is a 60-item version of the NEO Personality Inventory-Revised (Costa & McCrae, 2006) that provides a quick, reliable and accurate measure of the five domains of personality by providing the participants with 60 statements on which they have to indicate if they strongly disagree, disagree, are neutral, agree or strongly agree. The five domains of personality are: neuroticism, extraversion, openness to experience, agreeableness and conscientiousness. Each of these traits measures six subordinate dimensions.

Neuroticism measures the tendency of individuals to experience negative emotions such as anger, anxiety, quilt, frustration and depression. Individuals who score high on neuroticism are emotionally reactive and vulnerable to stress. They tend to interpret ordinary situations as threatening and are associated with low self-esteem and irrational thinking. The six subordinate dimensions of neuroticism are: anxiety, hostility, depression, self-consciousness, impulsiveness and vulnerability to stress. (Costa & McCrae, 2006; Tawfik & Rakha, 2012b; Wikipedia, n.d.)

Extraversion measures the engagement with the external world. Individuals with a high score on extraversion enjoy interacting with people and are full of energy. They tend to be enthusiastic and action-oriented individuals who like to talk and assert themselves. The six subordinate dimensions of extraversion are: warmth, gregariousness, assertiveness, activity, excitement seeking and positive emotion. (Costa & McCrae, 2006; Tawfik & Rakha, 2012b; Wikipedia, n.d.)

Openness to experience measures the imaginative tendency of individuals, their attentiveness to inner emotions and their sensitiveness towards art and beauty. Individuals who score high on openness to experience are intellectually curious, open to emotion and willing to try new things. Furthermore, they think and act in individualistic and nonconforming ways. The six subordinate dimensions of openness to experience are: fantasy, aesthetics, feelings, actions, ideas and values. (Costa & McCrae, 2006; Tawfik & Rakha, 2012b; Wikipedia, n.d.)

Agreeableness measures the more humane aspects of the personality, that is, general concern for social harmony. Agreeable individuals value getting along with others, are considerate, friendly, generous, helpful and willing to compromise. Furthermore, they have an optimistic view of human nature. The six subordinate dimensions of agreeableness are: trust, straightforwardness, altruism, compliance, modesty and tender mindedness. (Costa & McCrae, 2006; Tawfik & Rakha, 2012b; Wikipedia, n.d.)

Conscientiousness measures the tendency to show self-discipline, act dutifully and aim for achievement. High scores on conscientiousness indicate a preference for planned rather than spontaneous behavior and being organized and dependable. The six subordinate dimensions of conscientiousness are: competence, order, dutifulness, achievement striving, self-discipline and deliberation. (Costa & McCrae, 2006; Tawfik & Rakha, 2012b; Wikipedia, n.d.)

3.1.1 Route characteristics

Table 1 shows the characteristics of the ten route alternatives. The average travel time and travel speed are determined based on the obtained data of the experiment. The other characteristics are determined based on a satellite map of the area (Google Maps).

Table 1: Route characteristics of the route alternatives

OD-pair	Route	Avg travel time [min]	Avg travel speed [km/h]	Distance [km]	Number of intersections		Left turns	Merges and diverges	Horizontal curves
					Signalized	Unsignalized			
1	1	8.5	36.4	5.1	10	3	3	1	2
	2	8.4	43.3	6.0	5	4	4	5	3
2	3	15.2	42.6	11.1	5	2	3	1	30
	4	16.7	63.2	17.4	2	2	2	2	11
3	5	7.7	44.5	5.8	5	3	3	2	2
	6	9.3	37.8	5.5	8	3	2	1	2
4	7	10.2	29.5	5.0	5	3	4	1	0
	8	9.6	48.2	7.7	6	2	2	4	1
5	9	10.5	33.3	5.8	8	4	4	1	1
	10	8.0	34.0	4.7	3	1	3	2	6

OD-pair 1. Both routes have almost equal travel times, although route 2 has a slightly higher average speed. Furthermore, route 1 has notably more signalized intersections, while route 2 has more merges and diverges. The direction of both routes is towards the destination.

OD-pair 2. Route 3 is the shortest in terms of travel time. However, route 4 clearly outperforms route 3 based on travel speed. It should be noted that route 4 makes a significant detour and at the origin the direction of the route differs highly from the direction of the destination. Despite of this, route 3 has a lot more horizontal curves while route 4 outperforms route 3 concerning the number of signalized intersections.

OD-pair 3. Route 5 is shorter in terms of travel time and has a slightly higher average speed. In addition, it has less signalized intersections. However, route 5 is a route with high traffic volumes. Concerning the direction of the routes they are both kind of similar.

OD-pair 4. Route 8 is a little shorter in terms of travel time and has a significantly higher average speed. Besides, route 7 passes through the University Campus with the risk of getting stuck in campus traffic. However, route 8 contains more merges and diverges during the trip and makes a detour approaching the destination from a less direct direction.

OD-pair 5. Route 10 is clearly the shortest time route, while the average speed on both routes is quite similar. In addition, according to Tawfik and Rakha (2012a) this route uses an unpopular back road while route 9 passes through town. Note that route 10 has notably more horizontal curves than route 9. Furthermore, route 9 contains a left turn that leads to the opposite direction of the destination.

3.1.2 Limitations

- The data was collected under normal driving conditions on public roads. Therefore, the researchers had no control on traffic conditions and actual travel times. Run by run contextual data was not available, although it is likely that these conditions differ for each run. So each participant might have experienced different traffic conditions influencing his route choice behavior in the next run. Therefore, the choice situations as revealed in the data are not uniform.
- The perceived travel time of the participants for each route alternative is only obtained through a pre-task and post-task questionnaire and is not quantitative. Therefore, this data is highly aggregated as it is used for all 20 runs.
- During every run the five trips are completed consecutively (i.e. in a trip chain). Therefore, these five trips are made with the same feeling and state of mind by the decision maker. This might have influenced his decisions. Especially, when parts of the subsequent routes overlap.

For example, one might not want to take route 8 if he just took route 5 using the same road in order to vary the scenes.

- Although the participants were instructed to behave as naturalistic as possible and no incentives were related to the duration of the trips, the real need to arrive on time at a location is not present. In other words, there is no arrival time pressure and therefore the participants might have made their decisions in a different way than in the case this pressure would be present.

3.2 Dataset

The dataset consists of 2065 choice situations in which for each individual i and each run t the selected route as well as the experienced travel time is described. In addition, the results of the questionnaires are available providing for each individual i their age, gender, ethnicity (white versus colored), education, driving years, living years in Blacksburg, driven miles per year and the frequency of which a cell phone is used during trips. Furthermore, the scores of individual i on the five personality traits of the personal inventory are listed. In addition, the dataset provides information on the preferred route per OD-pair pq and the familiarity of each participant i with the route alternatives as stated by the participants. The stated familiarity is obtained before and after the participant has done the experimental runs, the route preference is obtained only after the participant has completed the experiment. Furthermore, the participants indicated for each OD-pair pq which route was faster in speed, contained less traffic, was shorter in travel time and was shorter in distance. The participant could also state that there was no difference between the two route alternatives on those criteria.

It should be noted that participant 5 did not complete all the experimental runs. In fact, he quitted the experiment after 13 runs. However, when investigating the choice situations separately, the data obtained through this participant can still be used. Another participant has been found to replace participant 5. Therefore, there is still complete data available for 20 participants.

3.3 Data-analysis

This section will provide the results of a short data-analysis. First, route choice patterns are identified and categorized. Subsequently, the observed inertial behavior is examined. This is followed by an analysis on the indifference band using individual's perceptions and their initial choices.

3.3.1 Route choice patterns

The daily route choices individuals make, reveal certain individual route choice patterns over time. This shows the day-to-day dynamics in route choice. While some travelers switch back and forth between routes in order to avoid congestion and minimize their travel time, others consistently take one route until some change forces them to choose another route (Tawfik, 2012). So, the route switching pattern of an individual differs from person to person. In general, a traveler does not switch routes as long as the corresponding trip time savings remain within his indifference band.

Tawfik identified four different driver types d based on the individual route choice patterns using the available dataset. These are shown in table 2, which includes a short description and illustration of the observed choice pattern. On the illustrations, a '0' represents a driver choosing one route alternative, and a '1' represents a choice for the other available route alternative. The frequency percentages are obtained using the real-world experiment dataset based on 2065 observations. They

indicate that route choice patterns belonging to driver type 1, 2 and 3 represent a large part of the dataset (26.7%, 29.5% and 34.3% respectively), while choice patterns of type 4 (9,5%) seem to be more rarely. This indicates that to some extent individuals have clearly a preference for a certain route alternative. In fact, in 56.2% of the examined choice patterns (i.e. driver type 1 and 2) individuals do not switch at all, after they have chosen a certain route alternative (based on single experiences on both routes (i.e. driver type 2) or just by randomly picking a route alternative which satisfies their expectations (i.e. driver type 1)).

A closer look reveals that for the switch-aversive driver types (i.e. type 1 and 2), driver type 1 is found the most on OD-pair 4 and OD-pair 5, while driver type 2 is found the most on OD-pair 2 and OD-pair 3. For the switch-sensitive driver types (i.e. type 3 and 4), driver type 3 is found the most on OD-pair 1 and OD-pair 2, while driver type 4 is found the most on OD-pair 1 and OD-pair 4. Interesting is that OD-pair 4 has not only the highest share in individuals choosing the same route alternative over and over again (i.e. type 1), but also in individuals choosing both route alternatives with approximately the same frequency (i.e. type 4). These driver types can be considered to be opposite. However, this finding might be explained by the fact that one of the route alternatives goes through the city center/university campus. One can imagine that some individuals like to just avoid this area, while others depending on the choice moment, that is, if they need to choose between these route alternatives close to the starting time of lectures at the university or not. This affects the throughput on this route alternative. This choice moment can easily alter about 10 minutes on subsequent days, resulting in the observed switching route choice pattern. Furthermore, on OD-pair 2, the highest shares of both type 2 and type 3 are found. As these driver types are more close to each other than type 1 and type 4, this is not considered to be a remarkable finding.

Table 2: Four identified driver types d based on individual route choice patterns

Driver type d	Description & Frequency percentage	Illustration
1.	A driver arbitrarily picks a route and is apparently satisfied with the experience. He continues to make the same choice over and over again. <table><tr><td colspan="2">*Frequency Type 1*</td></tr><tr><td>OD1</td><td>23.8%</td></tr><tr><td>OD2</td><td>9.5%</td></tr><tr><td>OD3</td><td>14.3%</td></tr><tr><td>OD4</td><td>47.6%</td></tr><tr><td>OD5</td><td>38.1%</td></tr><tr><td>Total:</td><td>26.7%</td></tr></table>	
2.	A driver arbitrarily picks a route and is apparently not satisfied with the experience. Therefore he tries the other route and decides that the first route was better. He continues in choosing the first route. <table><tr><td colspan="2">*Frequency Type 2*</td></tr><tr><td>OD1</td><td>19.0%</td></tr><tr><td>OD2</td><td>38.1%</td></tr><tr><td>OD3</td><td>47.6%</td></tr><tr><td>OD4</td><td>14.3%</td></tr><tr><td>OD5</td><td>28.6%</td></tr><tr><td>Total:</td><td>29.5%</td></tr></table>	

Driver type d	Description & Frequency percentage	Illustration
3.	A driver switches between two alternative routes. However, one route is used more than the other, which reflects his preference for this route. *Frequency Type 3* OD1 — 42.9% OD2 — 47.6% OD3 — 33.3% OD4 — 19.0% OD5 — 28.6% Total: — 34.3%	
4.	A driver switches between two alternative routes. He uses both routes with approximately the same frequency, reflecting the lack of preference towards any alternative. *Frequency Type 4* OD1 — 14.3% OD2 — 4.8% OD3 — 4.8% OD4 — 19.0% OD5 — 4.8% Total: — 9.5%	

3.3.2 Inertia

In order to determine if an inertial choice is made, the choices in which an individual i did not switch routes while this would have led to an expected decrease in travel time are identified. Therefore, the expected travel times by a certain individual i on both routes need to be estimated. It is assumed that for both route alternatives the average experienced travel time by an individual i up to run t represents this individual i's expected travel time for run t+1. Note that the expected travel time for the non-chosen route alternative does not change and therefore can be constant over several subsequent runs t (i.e. if the other route alternative is chosen repeatedly). In the case that there is not yet experience gained by individual i on one of the route alternatives (i.e. the individual i tried only one of the route alternatives up to moment t), the average travel time on that route experienced by all individuals during the specific peak hour is considered to be the expected travel time for run t+1.

Based on this definition, it is found that in 33% of the 2065 cases an individual should change their route choice for the next run t in order to decrease their travel time. In 70% of these cases the participants however did not change their route choice. This means that in 23% of all cases an inertial choice is made.

Figure 12 illustrates how an inertial choice can easily be identified from the data. It shows the expected (i.e. normal average) and experienced travel times for a certain individual i at all runs t at choice situation c. Note that the expected travel times of route B are always lower than those of route A. It appears that individual i made six inertial choices, at which the individual i stuck to the suboptimal route alternative. In addition, individual i chose five times to switch his route choice. Remark that most of the inertial choices are made within the first 10 runs.
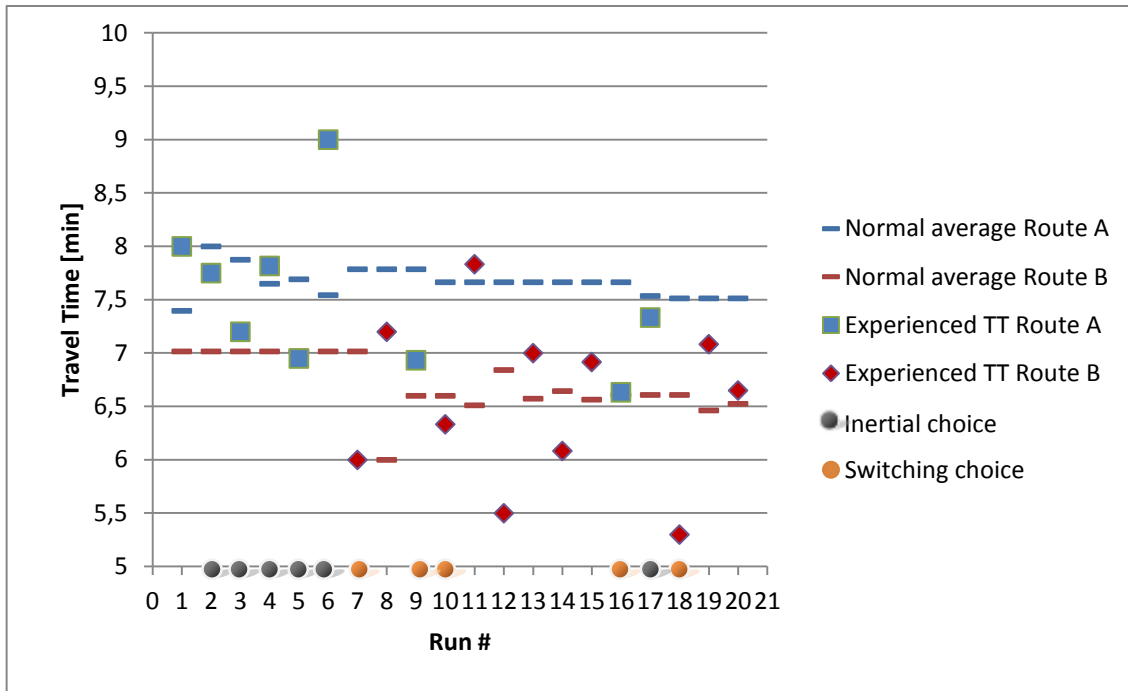
Figure 12: Example route choice data of 1 individual on a certain OD-pair showing inertia and switching.

Figure 13 shows the number of suboptimal inertial choices and route switches that are made per run summed over all participants. It becomes clear that most of the route switches take place during the second and third run after which a descending trend is noticeable. This indicates that at first most individuals try the different route alternatives to obtain experience on both routes and after a few trips they develop a preference for one of the route alternatives and stop switching. The fact that for the last runs less switches are made means that more individuals tend to stick to their choice in the end. However, regarding the suboptimal inertial choices, there is no clear trend visible. This suggests that individuals have identified the shortest route alternative after a few runs and then repeatedly choose this route. These findings are consistent with the notion of learning as elaborated in the theoretical framework (section 2.1.4). As a result, it can be hypothized that for the first few runs t inertial behavior occurs because of experimental choice behavior, while in the end these are conscious choices.
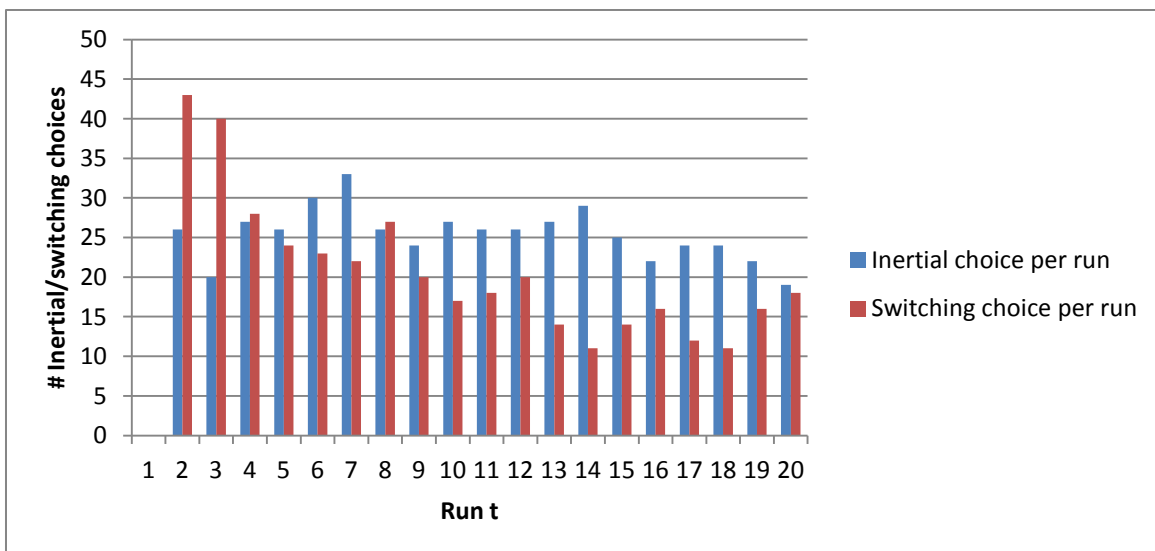
Figure 13: Inertial choices and switches per run (total choices per run: 100)

The time lost due to these inertial choices differs highly per participant, as becomes clear from table 3. Savings range from only about 1 minute to about 1.5 hour per participant summed over all 100 trips made. On average each individual i could save more than 20 minutes by making non-inertial choices. Furthermore, it shows that the number of inertial choices also highly differs per participant, ranging from only 5 to 68 inertial choices out of the total of 100 choice situations a participant has faced during the experiment. The number of inertial choices of participant 19 seems to be extreme. This participant has chosen the same routes over and over again on each run t, while the other route alternatives were expected to be shorter.

Table 3: Inertia and lost travel time per participant (total of 100 observations each)

Inertia and lost travel time per participant											
Participant	1	2	3	4	5*	6	7	8	9	10	11
Lost travel time [min]	0.9	24.0	31.4	8.1	8.9	21.8	11.9	7.9	7.8	5.2	23.6
Inertial choices [#]	5	34	34	14	5	25	11	18	7	15	19
Participant	12	13	14	15	16	17	18	19	20	21	*Avg*
Lost travel time [min]	4.2	18.4	14.8	33.2	24.6	2.8	24.7	89.8	43.7	40.6	*21.3*
Inertial choices [#]	17	20	32	38	18	15	21	68	36	31	*23.0*

As can be seen from table 4 the inertial choices per route range from 0.5% to 61%. Note that route 7 and 9 are rarely chosen. Furthermore, although route 10 is often chosen, only 0.5% of the choices are inertial choices. The same holds for route 5. This finding might be the result of these routes being the expected shortest route alternative in most cases. Therefore, inertial behavior (stick to the longer route) is often just not possible on these routes. When this fact is accounted for (last column of table 4), the percentage of inertial choices per route still seem to highly differentiate ranging from 6.5% to 96.2%. This suggests that inertial behavior might be influenced by route characteristics. So taking into account the findings of inertial choices per participant, this might suggest that inertial behavior is both dependent on individual characteristics and route characteristics of choice situation c.

Table 4: Inertia and lost travel time per route alternative

Inertia and lost travel time per route alternative							
OD-pair	Route	Total lost travel time [min]	Lost travel time per inertial choice [min]	Inertial choices [% of all choices on route]	Times route is chosen [#]	Times a inertial choice is possible on this route [#]	Inertial choices [% of possible inertial choices]
1	1	26.1	0.65	28.4	141	64	62.5
	2	59.4	0.55	39.7	272	133	81.2
2	3	29.6	0.62	18.4	261	88	54.5
	4	114.6	1.43	52.6	152	87	92.0
3	5	1.3	0.09	4.9	288	55	25.5
	6	108.5	1.43	60.8	125	79	96.2
4	7	31.6	0.96	44.0	75	41	80.5
	8	62.7	0.86	21.6	338	98	74.5
5	9	13.3	1.47	22.0	41	10	90.0
	10	1.1	0.57	0.5	372	31	6.5
Average:		*40.3*	*0.86*	*29.3*	*206.5*	*69*	*66*

3.3.3 Indifference band based on perception errors

After the participants completed the experiment of Tawfik, they were asked about their perceptions of travel time; which route is faster or is there no difference? Errors in these perceptions provide insights in the subconscious thresholds. If both route alternatives are being perceived as equally long by an individual i, while this individual i experienced a difference in average travel time on these route alternatives, his perception error is equal to the difference in experienced travel time.

However, if the longer route alternative as experienced by individual i is perceived as being the shorter route alternative, no exact perception error can be determined. This results from the fact that the dataset does not contain quantifiable values for the individual's perception of different routes. Therefore, in this case, the experienced difference in travel time can only provide an indication of the perception error. After all, at least this experienced difference was perceived erroneously.

So, for each individual i stating a perception of his experienced travel time on a certain OD-pair pq that is incorrect, the perception error is determined based on the average travel time difference this individual i has experienced on that specific OD-pair pq during the 20 runs; after all, his statement was based on all 20 runs of the experiment. The findings are shown in table 5 and table 6.

Table 5: Indifference bands based on perception errors per OD-pair pq

OD-pair pq	Average travel time difference on route alternatives using all 2065 observations [min]	# participants that are indifferent for travel time difference between route alternatives*	# participants that have an opposite perception to their experiences*	Average subconscious threshold (Based on average experienced travel time difference on individual level) [min]	Average choice frequency by indifferent individuals	
					Odd route	Even route
1	0.03	6	8	0.48	9.5	10.5
2	1.52	3	4	1.04	8.7	11.3
3	1.54	7	1	1.13	11.9	8.1
4	0.55	4	3	0.37	6.8	13.3
5	2.45	2	0	1.39	2.5	17.5
				Avg: 0.88**		

*As stated in the post-run questionnaire (i.e. after all experiment runs)
**Weighted average

Table 5 shows the findings on the subconscious thresholds for the individuals that perceived the travel time differences incorrectly detailed per OD-pair pq. It can be seen that on OD-pair 5, where the average time difference is the biggest, only 2 participants are indifferent for this average time difference. On the contrary, on OD-pair 1, where on average the travel times of both route alternatives are quite similar, there are 6 participants who consider these travel times to be indifferent and 8 participants who have an incorrect perception. These findings are as expected, as it is likely that a large travel time difference is more noticeable than a small travel time difference. Another remarkable fact is the high number of participants that are indifferent for travel time on OD-pair 3. These participants experienced a difference of 1.13 minutes, which is the second-highest difference, and are still indifferent. In addition, on OD-pair 4, which has relatively low travel time differences compared to the other OD-pairs, the number of individuals i with incorrect perceptions is comparable to that of OD-pair 2 and OD-pair 3. These findings suggest that there might be some situation dependent factors that influence the perceptions of individuals.

On average the participants that were indifferent for travel time chose both routes with about the same frequency. This is what would be expected; if people have no difference between two options they will on average choose both options with the same frequency. However, for OD-pair 5 (and OD-pair 4 to a lesser extend) the even route is chosen more frequently than the odd route. This indicates that on these routes there are some factors that outweigh the importance of travel time on route choice. Furthermore, it should be mentioned that on an individual level, great differences can be identified, which in the case of OD-pair 1, 2 and 3 balance each other out.

Table 6: Indifference bands based on perception errors per individual i

Individual i	Average subconscious threshold (based on perception errors) [min]*
111	1.37
112	0.98
113	0.30
114	0.97
115	-
116	0.61
121	0.90
122	0.52
123	-
124	-
125	0.56
211	-
212	0.83
213	-
214	0.52
215	0.39
221	0.32
222	0.78
223	1.02
224	1.16
225	0.97
Average**	0.76

*In calculating the average thresholds, the OD-pair/individual combinations in which no incorrect perception is stated, are not included.
**Weighted average based on the number of observations within the dataset per individual i.

Table 6 shows the findings on the subconscious thresholds for the individuals with incorrect travel time perceptions detailed per individual i. It can be seen that the thresholds range from as small as 0.30 minutes to as high as 1.37 minutes with an average value of 0.76 minutes. Note that the obtained values of table 5 and table 6 are highly aggregated, as the perception statements are only obtained at the end of the 20 experimental runs, while the indifference band is calculated using experienced travel times over all 20 runs. A more detailed overview of the thresholds per individual and OD-pair combination can be found in appendix B.1.

3.3.4 Indifference band based on inertia

The choice situations c in which an inertial choice is made, are used to indicate the inertia threshold. For each individual i and each OD-pair pq the maximum travel time difference of the inertial choices are determined. It is assumed that these maximum values provide some insight in the magnitude of the indifference band. Table 7 and table 8 show the averages of these maximum travel time differences per OD-pair pq and per individual i. A more detailed overview per individual and OD-pair combination can be found in appendix B.2.

It is found that for all five OD-pairs the inertia threshold seems to be higher than the perception threshold, as expected. Note that the inertia thresholds are all higher than 1 minute, while the perception thresholds are for some OD-pairs significantly lower than 1 minute. Furthermore, it is remarkable that the inertia threshold highly varies per individual i (ranging from 0.26 minutes to 2.11 minutes), while the values per OD-pair pq are more similar (ranging from 1.14 minutes to 1.61 minutes).

In general, the inertia threshold per individual i seems also to be higher than the perception threshold per individual i. The inertia threshold per individual i is on average 1.22 minutes, compared to a perception threshold per individual i of 0.76 minutes. This big difference might be caused by the fact that only a few individuals had incorrect perceptions in general, while inertial choices were observed for all individuals.

Table 7: Indifference bands based on inertia per OD-pair pq

OD-pair pq	Average inertia threshold* [min]
1	1.18
2	1.14
3	1.51
4	1.11
5	1.61
Average**:	1.31

*In calculating the average thresholds, the OD-pair/individual combinations in which no inertial choice is made, are not included.

**Weighted average based on the number of observations within the dataset per OD-pair pq.

Table 8: Indifference bands based on inertia per individual i

Individual i	Average inertia threshold* [min]
111	0.26
112	1.38
113	2.04
114	0.63
115	2.11
116	1.04
121	1.29
122	1.14
123	1.39
124	0.51
125	1.09
211	0.72
212	1.81
213	0.69
214	1.30
215	1.04
221	0.61
222	1.78
223	2.08
224	1.46
225	1.53
Average**:	1.22

*In calculating the average thresholds, the OD-pair/individual combinations in which no inertial choice is made, are not included.

**Weighted average based on the number of observations within the dataset per individual i.

3.3.5   Discussion and conclusions

The analysis on route choice patterns shows that driver types 1, 2, and 3 are most common within the available dataset, while type 4 seems to be relatively rare. Opposed to these findings, Tawfik, Szarka, House, and Rakha (2011) found percentages of 14%, 16%, 36% and 32% respectively for driver types 1 till 4 using data from a driving simulator experiment. Note the remarkable difference for driver type 4 (32% versus 9.5%). Therefore, it seems that individuals are more switch-aversive and expose a preference for a certain route alternative in real-life than in a simulated environment. However, this difference might just be a result of the fact that individuals' choice behavior can be affected by the experiment set-up, as the dynamics of the driver simulator lacks some realism. For example, in this particular driver simulator, there was no possibility to build different scenario's based on if the participant turned right or left at the different intersections and as a result, no landmarks were added to the network (Tawfik et al., 2011). This makes it harder for the participants of the experiment to obtain a reality alike experience of a certain route alternative and to compare

both route alternatives. It is likely that this results in a lack of preference for one of the route alternatives, leading to a higher percentage of switching behavior found by the simulator experiment of Tawfik.

In addition, the data-analysis shows that inertial behavior and the magnitude of both the inertia threshold and the perception threshold of individuals might be dependent on both personal attributes and route characteristics of the choice situation. These findings are in line with expectations as literature defines the indifference band as being an individual situation-specific threshold. Remember from the theoretical framework (section 2.1.7) that drivers will only alter their choice when a route characteristic, in this case travel time, is larger than this threshold. As inertia (not altering their choice) takes place within this threshold the finding that inertial behavior is also individual and situation-specific is quite logical.

Furthermore, perception thresholds of on average 0.89 minutes per OD-pair pq and 0.84 minutes per individual i are found. In addition, inertia thresholds of on average 1.31 minutes per OD-pair pq and 1.22 minutes per individual i are identified. These findings suggest that the inertia threshold might be indeed higher than the perception threshold as suggested in section 2.1.7 of the theoretical framework. Obviously, this difference is most visible when looking at the results per individual i as the effect of unconsciousness and consciousness is most influenced by the individual characteristics. For an elaboration on the quantification of the indifference bands, see chapter 10.

Now the dataset has become more familiar and insights in the issues of inertial behavior and the accompanying indifference bands are obtained, the next chapter will focus on identifying the explanatory attributes which might be of importance in modeling this inertial behavior and the indifference bands.

4 Attribute identification

This chapter will identify which attributes are explanatory for inertia and the indifference band. In order to do so, first empirical findings in literature are examined in section 4.1. These findings are used to come up with different variables that might be of importance. These variables are then, among others, used as independent variables in several regression analyses using different approaches (section 4.2). This way several models are obtained predicting satisficing behavior and other choice behaviors. Based on these models and their model performances (section 4.3), the main attributes that should be included in the final route choice model can be identified in the conclusion of this chapter (section 4.4). The most suitable regression approach will also be determined in this section.

4.1 Empirical findings in literature

This section lists the empirical findings that are found in literature. The most important findings about inertia and the indifference band are found in five papers. One of them (i.e. Vreeswijk et al. (n.d.)) also uses the data of the real-world experiment of Tawfik. The other literature findings are based on other datasets.

In their analysis of satisficing behavior Vreeswijk et al. (n.d.) analyzed satisficing behavior. They define satisficing behavior as an individual that should have switched his route choice in order to gain travel time savings, but did not switch. In other words, the individual stuck to the suboptimal route alternative. So, in fact, they use the same definition that is used for inertia in this research. With respect to their satisficing definition, they found the following:
- Based on the performance of the current choice relative to the expected performance of <u>choice alternatives</u>:
  - Roughly 1/4th of the choices made concerned satisficing behavior;
  - Small travel time differences and dominant non-travel time route attributes had a positive effect on the frequency of satisficing;
  - In satisficing choices indifference bands up to 4.5 minutes or 30% of the average travel times were found, while thresholds up to 1.3 minutes or 13% are more common;
  - Satisficing thresholds are systematic. However, the magnitude of these thresholds is probabilistic and depends on the choice set;
- Based on the performance of the current choice relative to expected performance of the <u>current choice</u>:
  - Roughly 1/2th of the choice made concerned satisficing behavior;
  - In satisficing choices indifference bands up to 3.3 minutes or 37% of the average travel times were found, while thresholds up to 1.2 minutes or 11% are more common;
  - Whether or not to switch hardly seemed to depend on bad travel time experiences on the current choice, but primarily on the availability of a route alternative which is expected to perform better
- Next to travel time, the travel time differences between alternatives, average travel speed and travel time reliability influences choice strategies;
- It appeared that respondents were loss-aversive rather than gain-seeking, which made them switch-aversive;

When Zhang (2006a) developed his SILK theory he identified several route search rules and route changing rules representing satisficing behavior and inertia. In deriving these rules, he has found the following (using the machine learning algorithm RIPPER), based on trips with an average distance of 14 miles and an average free flow travel time of 16 minutes:

- Drivers will only consider a specific route if its travel time is significantly lower (i.e. 21%) than the travel times on the other route alternatives;
- As the travel time difference becomes less apparent, other factors related to the simplicity of routes play also an important role;
- Drivers will change routes as long as travel time can be reduced by more than 39% (i.e. indifference band). If such a reduction is not possible, familiarity, commute time and distance, pleasure, delay and income are found to be important in route switching decisions.

Carrion and Levinson (2012) investigated route choice dynamics after link restoration and found that:

- Subjects react to day-to-day travel times on a specific route according to thresholds.
- Also subjects' previous experience and perception of the route alternatives influence the decision to abandon a chosen route.
- Both the indifference band with fixed thresholds and moving thresholds capture the dynamics of the data.
- Margins to classify early trips and late trips are asymmetric[2]. Late trips are more persistent in the subjects' moving set of travel times (i.e. the experienced travel times the subject can recall from previous trips) in comparison to the subjects' early trips.

Mahmassani and Liu (1999) found support for 'the notion that commuters' route switching decisions are predicted on the expectation of an improvement in trip time that exceeds a certain threshold, which varies systematically with the remaining trip time to the destination, subject to a minimum absolute improvement of about 1 minute'. Vreeswijk et al. (2013a) found evidence to assume an indifference band of on average 3-4 minutes on a total trip. In their research they used the perception error as indicator, which means that their findings apply to the subconscious thresholds. In addition, (Vreeswijk et al., n.d.) found conscious satisficing thresholds with a maximum of on average 3-5 minutes on a total trip. However, they found more commonly satisficing thresholds of on average 1.18 and 1.34 minutes, which are lower than their found subconscious thresholds. Reason for this is likely to be the different dataset that is used to obtain these values. As the datasets use different OD-pairs with different average trip lengths, these values might not be directly comparable.

The aforementioned findings indicate that a route choice model should include a mechanism that is based on the expected performance of the route alternatives. In order to include inertia in a route choice model, travel time differences between route alternatives, average travel speeds and distance as well as factors related to the simplicity of routes are found to be important. In addition, familiarity and previous experiences with the route alternatives are found to influence the decision to switch routes or not. Pleasure, delay and income are also found to be important in route switching decisions. However, in this research there is no data available on these issues. These findings and insights will be used to come up with relevant independent variables for the regression analysis.

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[2] Remember from the theoretical framework (section 2.3.7) that trips above the thresholds are referred to as late trips and trips below the threshold as early trips. Trips within the thresholds are regular trips. Individuals are more likely to leave the current route if the number of late trips increases, and more likely to stick with their current route if the number of early trips increases.

4.2 Regression analysis

In order to identify explanatory factors for inertia several stepwise regression analyses are performed on the available data. Useless observations were removed from the dataset based on a lack of information or lack of experience on a specific route alternative. This means that for some participants all 20 observations of a certain OD-pair pq are removed (i.e. driver type 1 as identified by Tawfik et al. (2011)). In addition, for all participants the choice situations in which a route is chosen for the first time (run 1) are removed. There were also three participants that did not fill in the post-task questionnaire and personality inventory. Therefore, the observations of these participants were also removed. Finally, 1193 data observations are used for the regression analyses obtained from 18 participants with an average of 66 observations per participant.

Vreeswijk et al. (n.d.) distinguished four choice strategies in observed route choice behavior (see table 9); minimizing by switching (CS1), minimizing by non-switching (CS2), satisficing (CS3) and compromising (CS4). They based this distinction on the expected travel times for both route alternatives by individual i at run t, which is determined as the average of all experienced travel times on the specific routes up to that run t. One should know that their satisficing strategy corresponds to the definition of inertia in this research. Based on those four observable strategies, different approaches are used for regression analysis in order to identify explanatory factors for choice behavior.

Table 9: Four choice strategies and their shares within the data-set*

Choice strategy	CS1	CS2	CS3	CS4
	Logical choice	Logical choice	Illogical choice	Illogical choice
	Should switch for TT gain	Should not switch for TT gain	Should switch for TT gain	Should not switch for TT gain
	Switches	Does not switch	Does not switch	Switches
	Minimizing	Minimizing	Satisficing	Compromising
Share of all choices [%]	9.0	52.5	23.4	9.5
Share of logical/illogical choices [%]	15.9	85.0	70.4	27.8

*Based on all 2065 observations, note that 5% of these choices consist of a choice made at run 1. For these runs no choice strategy can be determined

Since inertia is the main interest of this research, at first a model is obtained explaining this behavioral mechanism (i.e. the individual i did not switch and therefore lost travel time). However, as the model for inertia can only be applied in some of the choice cases (i.e. the cases in which the chosen route at run t-1 was in fact the longer route alternative and is expected to be the longer route alternative at run t as well), other approaches explaining for the other choice cases need to be obtained. After all, a strategy model capturing all four strategies, instead of only the inertial strategy, is expected to be more complete in predicting the final route choices of individuals.

Since the inertia model already accounts for the minimizing by switching strategy (i.e. non-inertia) and the inertia strategy, another model is developed in order to account for the other two choice strategies; the compromising strategy and the minimizing by non switching (i.e. non-compromising) strategy. This model is called the compromising model. Both the compromising model and inertia model are put together into a combined approach applying one of the two models depending on the individual's available choice strategies at run t. This combined method captures all four strategies and can be applied in a route choice model.

However, with another four strategies approach it is tried to come up with an explanatory model that captures all four strategies together at once instead of using two different models. Note that again, depending on the choice situation c an individual i has only two out of the four choice strategies available to use. Based on the experienced travel time of the choice at t-1 and the expected travel time for his current choice at t, individual i can make a logical choice and choose the route alternative with the lowest travel time by either switching or non-switching (CS1 or CS2), or individual i can make an illogical choice and choose the route alternative with the highest travel time by either switching or non-switching (CS3 or CS4). In other words, he can only behave according to one of the logical strategies or one of the illogical strategies in choice situation c at time t. This makes it interesting to also search for a model predicting if an individual makes a logical or illogical choice, capturing these choice strategies all together. Note that a used choice strategy is defined to be logical or illogical based on the travel times of the different route alternatives in which the shorter route alternative is identified as being a logical choice. Based on other criteria choosing the shorter route alternative might be actually illogical instead of logical. However, within this research a logical or illogical choice is always defined based on the travel time criteria.

The performance of the choice strategy model might be improved by making some modifications in the way the model is applied which allows this model to only predict one of the two available choice strategies (out of the four choice strategies the model can predict) in a certain choice situation. This is accounted for in an adapted choice strategies approach.

Each approach asks for a different dependent variable, which are shown in table 10. Since these are categorical variables a linear regression method does not provide sensible results. Instead a logistic regression method must be used; the binary logistic regression method is applied in case the independent variable consists of two categories, the multinomial logistic regression is applied in case the independent variable consists of more than two categories. In this research the different categories correspond to the different choice strategies.

Table 10: Dependent variables corresponding to the different approaches of stepwise regression analyses

Values dependent variable	Inertia model	Compromising model	Combined model	Four choice strategies model	Four choice strategies adapted	Illogical model
0	Non-satisficing choice	Non-compromising choice	n/a	CS1	n/a	Logical choice
1	Satisficing choice	Compromising choice	n/a	CS2	n/a	Illogical choice
2	n/a	n/a	n/a	CS3	n/a	n/a
3	n/a	n/a	n/a	CS4	n/a	n/a

*n/a stands for 'not applicable'

The independent variables that are used in all approaches are shown in table 11 and exists of variables on driver demographics, driver personality traits, driver experience, choice situation and driver-choice combination. These variables are chosen based on the available data, the variables used in Tawfik's papers and the findings of the data-analysis and literature as identified in section 4.1 and chapters 2 and 3.

Table 11: Independent variables of stepwise regression analyses

Variable	Variable description	Variable values
Variables of driver demographics		
Age_i**	Age of participant i	18 to 65
$Gender_i$	Gender of participant i, 0=male, 1=female	0 or 1
$Ethnicity_i$	Ethnicity of participant i, 0=white, 1=non-white	0 or 1
$Education_i$	Education of participant i, 0=high school graduate or GED, 1=Some college or technical school graduate, 2=college graduate, 3=earned a graduate degree	0, 1,2 or 3
Driving years$_i$**	Number of years participant i has been a licensed driver	2 to 57
Driving miles$_i$	Annual number of miles participant i drives (thousands)	2 to 35
$Residency_i$	Number of years participant i has been residing in the area	1 to 56
Variables of driver personality traits		
N_i	Neuroticism of participant i	7 to 30
E_i	Extraversion of participant i	19 to 43
O_i	Openness to experience of participant i	20 to 31
A_i	Agreeableness of participant i	22 to 42
C_i	Conscientiousness of participant i	26 to 47
Variables of driver experience*		
$TTprc_{ic}$	Percentage difference in mean experienced travel times by driver i between the two alternatives of choice situation c	0.005 to 0.292
$TSprc_{ic}$	Percentage difference in mean experienced speed between the two alternative routes of choice situation c	0.020 to 0.481
$\Delta TTexp\_abs_{ict}$	Absolute difference in the average of experienced travel times up to run t by driver i between the two alternatives of choice situation c	0.053 to 2.625
$Performance_{ic,t-1}$	Performance of the chosen route alternative of choice situation c at run t-1 experienced by driver i, expected travel time compared to experienced travel time, 0=performance is better than expected, 1=performance is worse than expected	0 or 1
$Switches_{ict}$	Number of switches driver i made during the experimental runs at choice situation c up to run t	1 to 13***
Variables of choice situation		
Movement category$_c$	Category of the movement based on road type in choice situation c, 0=rural/highway movement, 1=city road movement	0 or 1
Straight distance$_c$	Straight distance in kilometers between OD-pair of choice situation c	3.2 to 6.8
$\Delta TTabs_c$	Absolute difference in average travel time between route alternatives of choice situation c	0.1 to 2.5
$\Delta TT\_prev_{ic,t-1}$	Difference in average travel time between the two alternatives of choice situation c at run t-1 for driver i, reference is shortest route alternative (value=0)	0 to 2.5
$\Delta TD\_prev_{ic,t-1}$	Difference in travel distance between the two alternatives of choice situation c at run t-1 for driver i, reference is route alternative with shortest distance (value=0)	0 to 6.3
$\Delta TS\_prev_{ic,t-1}$	Difference in travel speed between the two alternatives of choice situation c at run t-1 for driver i, reference is route alternative with lowest speed (value=0)	0 to 18.7
$\Delta Intersection\_prev_{ic,t-1}$	Difference in number of intersections between the two alternatives of choice situation c at run t-1 for driver i, reference is route alternative with least intersections (value=0)	0 to 8
$\Delta Left turn\_prev_{ic,t-1}$	Difference in number of left turns between the two alternatives of choice situation c at run t-1 for driver i, reference is route alternative with least left turns (value=0)	0 to 2
$\Delta Merges$ and $diverges\_prev_{ic,t-1}$	Difference in number of merges and diverges between the two alternatives of choice situation c at run t-1 for driver i, reference is route alternative with least merges and diverges (value=0)	0 to 4
$\Delta Horizontal curves\_prev_{ic,t-1}$	Difference in number of horizontal curves between the two alternatives of choice situation c at run t-1 for driver i, reference is route alternative with least horizontal curves (value=0)	0 to 19
Time of day$_c$	Time of day choice situation c occurs, 0=morning peak hour, 1=afternoon peak hour, 2=evening peak hour	0, 1 or 2
Variables of driver-choice combination		
Average familiarity$_{ic}$****	Stated average familiarity of driver i with the two routes of choice c prior to the experiment, 0=very unfamiliar, 4=very familiar	0 to 4
Maximum familiarity$_{ic}$ ****	Stated maximum familiarity of driver i with the two routes of choice c prior to the experiment, 0=very unfamiliar, 4=very familiar	0 to 4
$Preference_{ic,t-1}$	Prior to the experiment stated preference for a route alternative of participant i in choice situation c related to the route choice at time t-1, 0=preference for route that was not chosen at t-1, 1= preference for route that was chosen at t-1	0 or 1

*percentage difference is calculated as the difference between experiences on the two routes divided by the average of the two routes

**Because of high correlation between age and driving years, these variables were not allowed to be in the same model at the same time

*** Driver that have not experienced both routes were dropped from the analysis because of missing experience data

**** Because of opposite coefficients of average familiarity and maximum familiarity, these variables were not allowed to be in the same model at the same time.

The obtained regression models can be applied on the available observations (i.e. choice situations) in order to obtain probabilities that a certain choice strategy will be exposed at that choice situation c. First, the regression model will provide an outcome for each run t at all choice situations c. This outcome is a number that must be seen relatively to the reference category of the dependent variable, which in this research is always chosen to be the category indicated with 0 in table 10. These obtained outcomes can be translated into the probability P that the corresponding category (cat) will expose in choice situation c at run t (i.e. category 1 in binary cases and 1,2, or 3 in the multinomial case) using the following formulas:

Binomial regression: $P_{ct} = \frac{e^{outcome_{cat}}}{1 + e^{outcome_{cat}}}$

Multinomial regression: $P_{ct} = \frac{e^{outcome_{cat}}}{\sum_{cat=0}^{3} e^{outcome_{cat}}}$

And $outcome_{cat} = constant + \sum_j (\beta_j * X_{ctj})$

where X_{ctj} is the value of a certain attribute j at run t in choice situation c and β_j is the weight of this attribute. Based on these probabilities a prediction of the used choice strategy can be made (elaborated upon in section 4.3). Note that both regression methods develop models by including attributes that optimize the explanatory power (i.e. model fit) by minimizing the error in the predictions of the model and therewith minimizing the error in the probabilities.

The probabilities P of all categories together should account for a total of 100%. Therefore, the probability of the occurrence of the reference category can be calculated using the probability of occurrence of the other categories.

4.2.1 Inertia approach

In order to predict if an inertial choice is made, an inertia model is developed. The inertia model is obtained by performing a stepwise binary logistic regression analysis based on the observations in which inertia is a possible choice strategy (427 observations). The used criteria for attribute entry or removal at each step are a probability of F of 0.05 and 0.10 respectively, using the Likelihood Ratio statistic. The obtained model (see table 12) has an R^2 of 0.403. The model includes eight variables; six of them are individual dependent, the other two are related to route characteristics and choice situation. The model will only be applied on the observations in which inertial behavior is a possible choice strategy.

Table 12: Obtained inertia model from a binary logistic regression analysis

Model	Inertia model	
R^2	0.403	
	Beta	Significance
Constant	11.084	0.000
Time of day$_c$=0	Reference	
Time of day$_c$=1	-1.173	0.012
Time of day$_c$=2	3.649	0.000
Ethnicity$_i$=0	Reference	
Ethnicity$_i$=1	-3.694	0.008
Education$_i$=0	Reference	
Education$_i$=1	1.788	0.196
Education$_i$=2	0.108	0.848
Education$_i$=3	-1.780	0.006
Driving years$_i$	0.148	0.000
C_i	-0.143	0.000
Maximum familiarity$_{ic}$	-0.486	0.001
ΔTT_prev$_c$	-0.952	0.000
Residency$_i$	-0.201	0.000

* Time of day$_c$, Ethnicity$_i$ and Education$_i$ are categorical variables. Each category in the model functions as a dummy variable. The category indicated with 'Reference' is the reference category (i.e. Beta=0).

The obtained model indicates that during noon peak hour individuals are more likely to make a non-inertial choice compared to the morning peak, while during evening peak hour they are more likely to make an inertial choice. This might be explained by the fact that people might want to spend their noon break time in an efficient way and therefore do not want to lose any time during their trip or are just better at assessing the choice options at this time of day. In the evening an individual might be tired from working all day and just want to go home. In addition, his judgment skills might be decreased at this time of day.

Furthermore, white individuals are more likely to make a non-inertial choice than non-white individuals. The model also suggests that individuals with the highest education level have a higher probability of making a non-inertial choice, while individuals of the other education levels are more likely to perform inertial behavior. This seems logical, as higher educated individuals might be better in assessing the differences between the route alternatives, leading to more optimal choices.

Furthermore, the model indicates that the higher the individual scores on conscientiousness, the higher the probability that an individual will make a non-inertial choice. Since conscientious people are efficient and aim for achievement, it is assumable that they are more experienced in making thoughtful decisions and try to pick the shortest route alternative.

An individual having more driving years leads to a higher probability of inertial behavior, while individuals that are more familiar with the route alternatives or reside for a longer time period in the area of the OD-pairs they are more likely to make a non-inertial choice. Individuals with a higher familiarity with the route alternatives and the surrounding network (by residing in the area) have gained more knowledge about the traffic state on and performance of the different routes alternatives and are therefore able to make a better judgment to base their decision on.

Lastly, if a higher travel time difference compared to the shortest route alternative is experienced during the previous choice situation, it is more likely that an individual is going to make a non-inertial choice, which is switching to the shortest route alternative. This is in line with the expectation that travelers want to use the shortest route alternative.

Overall, the inertia model seems to contain attributes that explain inertial behavior in an intuitive and explainable manner.

4.2.2 Compromising approach

In order to predict if a compromising choice strategy is used, an explanatory compromising model is developed by performing a stepwise binary logistic regression analysis based on the observations in which compromising is a possible choice strategy (765 observations). The used criteria for attribute entry or removal at each step are a probability of F of 0.05 and 0.10 respectively, using the Likelihood Ratio statistic. The obtained model (table 13) has an R^2 of 0.232, which is significantly lower than the R^2 of the inertia model. The model includes six variables; five of them are individual dependent, one is related to the travel time route characteristic. The model will only be applied on the observations in which a compromising choice strategy is possible.

Table 13: Obtained compromising model from a binary logistic regression analysis

Model	Compromising model	
R^2	0.232	
	Beta	Significance
Constant	-9.527	0.000
$Gender_i$=0	Reference	
$Gender_i$=1	1.042	0.001
$Education_i$=0	Reference	
$Education_i$=1	1.981	0.000
$Education_i$=2	1.509	0.000
$Education_i$=3	-0.725	0.113
E_i	0.113	0.000
C_i	0.129	0.000
$\Delta TTabs_c$	-0.655	0.000
Maximum $familiarity_{ic}$	-0.255	0.018

*$Gender_i$ and $Education_i$ are categorical variables. Each category in the model functions as a dummy variable. The category indicated with 'Reference' is the reference category (i.e. Beta=0).

The obtained model shows that females are more likely to make a compromising choice than males. Furthermore, individuals with the highest education level have a higher probability of making a non-compromising choice which is in line with the expectation that higher educated people are more likely to make logical choices.

Higher individual scores on extraversion and conscientiousness both lead to a higher probability of using a compromising choice strategy. Extravert individuals enjoy being involved in a lot of different activities and situations to get energized. Therefore they are expected to choose a lot of different route alternatives in each choice situation. This means that they will not always stick to the best choice option, but switch regularly resulting in a higher probability of making compromising choices. According to the inertia model conscientious individuals tend to switch to the shortest route alternative, while according to the compromising model conscientious individuals are more likely to make compromising choices, which is switching to the longer route alternative. This implies that a higher level of conscientiousness makes it more likely that an individual is going to switch routes. A possible explanation for this is that conscientious individuals might be more sensitive for small differences in several different variables and therefore switch more often.

Individuals who are more familiar with the route alternatives tend to stick with the shortest route alternative which is in line with the inertia model that indicates that these individuals switch to the shortest route alternative.

Lastly, the bigger the difference in absolute travel time between the two route alternatives, the more likely it is that individuals will choose the shortest route alternative. This seems logical as with a bigger difference it becomes easier for the decision maker to identify which route is the shortest route alternative.

4.2.3 Combined approach; inertia and compromising

In the combined approach, both the compromising model and inertia model as elaborated in the previous sections are applied in order to predict which choice strategy is used. These models are developed based on two different datasets dividing the available data based on the fact if at t-1 a suboptimal or optimal choice is made by a certain individual i. Depending on this choice, one of the two models is applied. However, in the special case that the route alternative that was expected to be the shortest route alternative, becomes the expected longest route alternative this criteria is not sufficient. In addition, the chosen route at run t-1 needs to be the shortest or longest route alternative at run t as well. If not, the sub-model choice needs to switch. So, in fact, the combined approach uses the inertia model and compromising model in order to complement each other in predicting the used choice strategy by an individual i at run t in choice situation c.

4.2.4 Four choice strategies approach

In order to predict which of the four choice strategies is used by applying only one model instead of two models (as in the combined approach), a four choice strategies model is developed using a stepwise multinomial logistic regression analysis. This model is based on all 1193 observations from the dataset. The used criteria for attribute entry or removal at each step are a probability of F of 0.05 and 0.10 respectively, using the Likelihood Ratio statistic. The obtained model (see table 14) has an R^2 of 0.427, which is comparable to the satisficing model. The model includes 15 variables, all individual and/or choice situation related.

Table 14: Obtained choice strategy model from a multinomial logistic regression

Model	Four choice strategies					
R^2	0.427					
	CS2 (Minimizing)		CS3 (Satisficing/Inertia)		CS4 (Compromising)	
	Beta	Significance	Beta	Significance	Beta	Significance
Constant	56.820	0.000	-14.065	0.378	11.222	0.522
$\Delta TTabs_c$	0.495	0.001	-0.739	0.000	-0.124	0.479
E_i	-0.485	0.000	0.133	0.311	-0.022	0.883
Driving miles$_i$	$0.250E^{-3}$	0.000	$0.117E^{-4}$	0.840	$0.281E^{-5}$	0.967
Driving years$_i$	-0.006	0.905	0.272	0.000	0.037	0.616
Preference$_{ic,t-1}$=0	-0.971	0.000	-0.600	0.011	-0.633	0.014
Preference$_{ic,t-1}$=1	Reference		Reference		Reference	
Ethnicity$_i$=0	-18.398	0.000	0.096	0.982	-4.107	0.399
Ethnicity$_i$=1	Reference		Reference		Reference	
Time of day$_c$=0	1.218	0.033	-0.773	0.203	-0.656	0.368
Time of day$_c$=1	-0.840	0.375	5.627	0.000	1.017	0.435
Time of day$_c$=2	Reference		Reference		Reference	
Gender$_i$=0	-1.022	0.076	0.389	0.594	-0.345	0.658
Gender$_i$=1	Reference		Reference		Reference	
Education$_i$=0	3.696	0.105	5.758	0.024	1.939	0.498
Education$_i$=1	-7.513	0.000	3.784	0.101	-1.003	0.697
Education$_i$=2	-2.290	0.004	-0.787	0.362	-0.877	0.412
Education$_i$=3	Reference		Reference		Reference	
Residency$_i$	-0.118	0.114	-0.340	0.000	-0.085	0.387
N_i	-0.812	0.000	0.249	0.231	-0.073	0.762
O_i	0.430	0.000	0.154	0.206	-0.084	0.599
C_i	-0.560	0.000	0.019	0.898	-0.060	0.727
$\Delta TSabs_c$	-0.026	0.216	0.081	0.001	$0.369E^{-3}$	0.989
Average familiarity$_{ic}$	0.144	0.263	-0.454	0.001	-0.032	0.847

*Preference$_{ic,t-1}$, Ethnicity$_i$, Time of day$_c$, Gender$_i$ and Education$_i$ are categorical variables. Each category in the model functions as a dummy variable. The last category of each variable is the reference category (i.e. Beta=0).

The model shows that the bigger the absolute travel time difference between the two route alternatives, the more likely that a person is going to minimize. In contrary, in a choice situation with a big travel speed difference individuals are more likely to make an illogical choice. This indicates that people might prefer routes with higher travel speeds even if this means their trip will take longer. The number of annual driving miles[3] contributes the most to a minimizing strategy, which might be explained by the fact that individuals that drive a lot have more experience in making route choices. Besides this, they are able to save more travel time in total. The number of driving years contributes mostly to inertial behavior. One might think this is remarkable since those individuals might have a lot of experience in making route choices. However, a higher number of driving years complies in general to a higher age. Older individuals might not feel the urgency to save travel time anymore and other factors have become more important in their route choice (e.g. familiarity or variables related to simplicity of the route). Ethnicity turned out to have a high impact on the fact if an individual is likely to minimize or not. Apparently white individuals are less likely to minimize than non-white individuals while they are slightly more likely to make an inertial choice. Furthermore, the model suggest that male individuals are less likely to minimize by non-switching than females, instead they tend to make inertial choices more.

If individual i has a preference for a route that was not chosen at run t-1, this individual is more likely to minimize by switching (CS1) than by non-switching, and inertia or compromising, which might be logical if one assumes the route with the shortest travel time is preferred in most cases.

Furthermore, the model indicates that in the morning peak people are more likely to minimize, while during the noon peak people are more likely to make an inertial choice or compromise. So in the morning people might like to use the shortest travel time alternative in order to start their journey as late as possible to still arrive at their destination on time, while during their lunch break this is of less importance. Note that this relation is opposite to the relation found in the inertia model.

The higher an individual i scores on extraversion, neuroticism and conscientiousness, the less likely a strategy of minimizing by non-switching or compromising is used, while openness to experience has the opposite effect on the minimizing strategy.

Lastly, the more familiar an individual i is with the available route alternatives prior to the trips, the more likely he is to use a minimizing strategy. This is quite logical as he knows the characteristics of both routes already and is therefore able to make better decisions.

One should note that, since the three sub-models all compare to reference category CS1 (minimizing by switching), it would be expected that the model of CS2 has less extreme beta values as this strategy is very similar to CS1. Remarkably, this is not the case. Therefore, the obtained model feels somewhat counter intuitive at some points, although most of the effects of the variables on the different choice strategies can be explained to some extent. This might occur due to the fact that at a choice moment the decision maker has only two of the four strategies available, as mentioned earlier. The model attributes on individual characteristics and route characteristics do not account for this fact. So apparently, this approach is not very suitable for the intended application. Therefore, in order to increase the accuracy and suitability of the model, an adapted approach is developed in the next section.

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[3] Note that the coefficient of the driving miles variable is very small. This occurs because the driving miles is in most cases a very large number. Therefore the effect on the outcome of the model is significant

4.2.5 Adapted approach

In the adapted approach the four choices strategy model is used as starting point. It is then decided per run t which two strategies from this model are available based on the fact if the choice at time t-1 was an optimal or suboptimal choice. The probabilities of occurrence of these two available strategies (obtained by the basic choice strategy model) are than extrapolated to ensure that together the available choice strategies make up for 100% of the possible choice strategies. After this adaptation the choice strategy that will be used at run t is predicted.

It is assumed that a model approach taking the availability of the choice strategies into account will increase the performance of the four choice strategies model as the predictions are limited to only the available choice strategies at a certain run t and predictions will therefore be more realistic.

Note that it is not possible to recalibrate the coefficients of the model based on splitting the data according to the available choice strategies due to the use of a multinomial model (the three sub models cannot be seen separately). If one wants to recalibrate the coefficients another approach would be needed, splitting the model into separate sub models using binary logistic regression, which actually is done in the combined approach as elaborated in section 4.2.3.

4.2.6 Illogical choice approach

In order to predict if an illogical choice will be made at a certain run t of choice situation c, an illogical choice model is developed by performing a stepwise binary logistic regression analysis. This model is based on all 1193 observations from the dataset. The used criteria for attribute entry or removal at each step are a probability of F of 0.05 and 0.10 respectively, using the Likelihood Ratio statistic. The obtained model (see table 15) has an R^2 of 0.341, which is a little lower than the R^2 of the inertia model and four strategies model. The obtained model includes 14 variables; besides individual dependent variables and variables related to route characteristics, also the number of made switches made by individual i at run t, which is a factor of driver experience, turned out to be of importance.

Table 15: Obtained logical/illogical choice model from a binary logistic regression

Model	Logical versus illogical	
R^2	0.341	
	Beta	Significance
Constant	-27.924	0.000
Time of day$_c$=0	Reference	0.000
Time of day$_c$=1	-3.568	0.000
Time of day$_c$=2	2.761	0.000
Ethnicity$_i$=0	Reference	
Ethnicity$_i$=1	11.775	0.000
Education$_i$=0	Reference	
Education$_i$=1	-1.457	0.000
Education$_i$=2	5.607	0.000
Education$_i$=3	0.814	0.027
Driving miles$_i$	-0.171E^{-3}	0.000
N_i	0.528	0.000
E_i	0.413	0.000
O_i	-0.237	0.000
A_i	-0.192	0.001
C_i	0.236	0.000
Switches$_{ict}$	-0.090	0.009
$\Delta TTabs_c$	-0.824	0.000
$\Delta TSabs_c$	0.045	0.003
Maximum familiarity$_{ic}$	-0.619	0.000
Age$_i$	0.079	0.000

* Time of day$_c$, Ethnicity$_i$ and Education$_i$ are categorical variables. Each category in the model functions as a dummy variable. The category indicated with 'Reference' is the reference category (i.e. Beta=0).

According to this model an individual is more likely to make a logical choice during the noon peak and an illogical choice during the evening peak compared to the morning peak. This is opposite to the findings in the four choice strategies model, but consistent with the inertia model.

Furthermore, the model indicates that a non-white individual is more likely to make an illogical choice than a white individual, which is also in contrast with the four choice strategies model.

It is remarkable that the model indicates that the two least educated categories are more likely to make a logical choice than the two highest educated categories. Intuitively, one might expect the opposite. However, one explanation might be that the lower educated individuals think more simplistic and just choose the shortest route, while the higher educated individuals make more complex choices by considering a lot of factors and end up making a suboptimal choice as it might score better on the other factors.

The illogical model is the only model that includes all the five personality traits. Neuroticism, extraversion and conscientiousness of an individual i increase the likelihood of making an illogical choice, while openness to experience and agreeableness decrease this likelihood. Individuals that are open to experiences are curious about the alternatives and try both options. Therefore they might be able to make more logical choices. Agreeable persons are friendly, generous and helpful, and trusts information that they obtain and the collective judgment of others. Therefore, in general, it makes sense that they are more likely to make logical decisions. Extravert individuals enjoy being involved in a lot of different activities and situations to get energized. Therefore they are expected to choose a lot of different route alternatives in each choice situation. This means that they will not always stick to the best choice option, but switch a lot resulting in a higher probability of making illogical choices. Conscientious individuals have a preference for planned and rational behavior rather than impulsive behavior and aim for achievement. Therefore it is more intuitively to expect them to be more likely to make logical decisions. However, in aiming for achievement they might consider a lot of issues in making their choice, resulting in a very complex decision making process. Remember, the distinction of logical and illogical choices is made based on the simple difference in expected travel time between the route alternatives. Thus, this complexity might lead to an improved probability of making illogical choices. Lastly, neurotic individuals have the tendency to experience negative emotions relating ordinary situations. They might be therefore less satisfied with their choices and tend to switch often, leading to a higher probability of making illogical decisions.

Furthermore, a higher number of experienced switches increases the probability of making a logical choice as would be expected, since the individual has more knowledge about the different choice options in order to assess them correctly.

The model also suggest that the bigger the absolute travel time difference between the two route alternatives, the more likely that a person is going to make a logical choice. In contrary, in a choice situation with a big travel speed difference individuals are more likely to make an illogical choice. As mentioned before, this indicates that people might prefer routes with higher travel speeds even if this means their trip will take longer.

Another issue that is shown by the model is that a higher familiarity with one or both of the route alternatives prior to the experiment leads to a higher probability of making logical choices. The individual knows the characteristics of the routes already and can make a decision based on his experiences. In case he is not familiar with one of the routes he might try this one and might be more alert on the route characteristics compared to the familiar route and therewith assess the differences more accurately in order to make his choice.

Lastly, the model suggests that a higher age leads to a higher probability of making an illogical decision. As mentioned with the choice strategy model, older individuals might not feel the urgency to save travel time anymore and other factors might be more important in their route choice.

It can be concluded that the effect of all attributes on making a logical or illogical choice are in line of the expectations or can be explained to some extent.

4.3 Performance of regression models

All six models are tested on their performance to correctly predict the behavior that was found in the data of Tawfik. Based on the found probabilities P_{ct} for a certain choice strategy on each observation, a prediction is made for that observation using a uniformly distributed random number between 0 and 1 which defines which category will be predicted. For example, category 0 (i.e. non-inertia, non-compromising, CS1 or logical choice) has a probability P_{ct} of 0.8345 and category 1 has a probability P_{ct} of 0.1655; if the random number is smaller than 0.8345 category 0 will be predicted, otherwise category 1 will be predicted. This predicted choice behavior is compared to the observed choice behavior in each observation and a percentage of correctly predicted cases is determined. Since a random number is used, it is necessary to repeat the predictions several times and average the obtained percentages. If a model made an incorrect prediction at a certain run t, the value of the model attributes for run t+1 are updated using the actual experienced characteristics of run t, despite of the incorrect prediction. In other words, the model is reset after each prediction. After all, no information for updating is available for the incorrect prediction. Note that this is only a restriction because of using the available dataset; for instance, in performing a micro-simulation this is not necessary. As a result of this resetting, the performance indicator used in this research applies to predictions of individual choices for the next run t and not for the complete choice pattern over all runs t. However, one can imagine that if the choice for each next run t is correctly predicted, the final choice pattern is also likely to be correctly predicted, although one incorrectly predicted case could mess up the whole predicted choice pattern.

Remember that the inertia model and compromising model will only be applied on the observations in which inertia or compromising respectively is a possible choice strategy. If this is not the case, it is assumed that a non-inertial or non-compromising choice is made and category '0' is predicted.

As there might be some differences in predictability between the different trips, the performance of the different models on each OD-pair pq is examined. In addition, since individuals might be exploring the route alternatives that are available to them at first, there might be a difference in predictability of the choice behavior between the first and last 10 runs. Therefore the performance of the models is also detailed for the first and last 10 runs of each OD-pair pq. Lastly, one can imagine that there might be some differences in predictability for the different driver types d as identified by Tawfik et al. (2011). Therefore, the model performances are obtained per driver type d as well.

For comparison, the model performance of the vastly used utility maximization theory in which travel time is used as the only model attribute (i.e. shortest path theory) is also determined. Since the choice strategies on which the regression models are developed, are based on the expected travel times for the different route alternatives for the specific time of day (i.e. morning, noon or evening peak hour) the trip is made, the shortest path theory is also applied using the average travel times of the different route alternatives for each time of day.

Table 16: Performance of the regression models

Correctly predicted route choices	Inertia model	Compromising model	Combined model	Four choice strategies model	Four choice strategies adapted	Illogical model	Utility Maximization / shortest path theory
OD-1 [%]	55.83	67.44	62.30	38.84	65.84	55.78	38.11
OD-2 [%]	64.98	66.34	65.80	49.30	75.43	60.79	65.96
OD-3 [%]	65.88	75.67	72.73	54.69	77.44	65.87	76.09
OD-4 [%]	72.91	63.02	67.91	46.04	72.28	52.29	32.02
OD-5 [%]	45.33	83.00	77.12	64.31	81.17	78.88	87.50
First 10 runs t [%]	58.58	67.88	64.04	47.29	72.27	60.65	52.51
Last 10 runs t [%]	67.66	75.05	72.71	52.85	76.07	64.23	67.85
Driver type 1 [%]	-	-	-	-	-	-	-
Driver type 2 [%]	86.35	83.14	84.02	66.69	89.23	68.05	72.21
Driver type 3 [%]	50.92	63.27	58.15	41.20	65.88	59.42	52.42
Driver type 4 [%]	55.26	55.56	55.42	25.07	51.97	55.20	55.20
Total correctly predicted [%]	62.97	72.10	68.89	50.43	74.36	62.78	61.19

Table 16 shows that over all the adapted four choice strategies model has the highest percentage of correctly predicted behavior. In contrary, the four choice strategies model without adaptations performs the worst of all models. So, the adaptations made to the four choice strategies model did improve the performance of the model significantly, as was expected. Note that both the inertia model and the compromising model perform reasonable in predicting inertial and compromising behavior respectively. When they are combined into one approach in the combined model, the performance lies in between the performances of the separate models. Note that the performance of the combined model is closer to the compromising model, as this model is based on a larger part of the combined dataset. These findings are in line with expectations.

Regarding the different OD-pairs all models show a high variability in correctly predicted cases. The performances on OD-pair 3 and 5 are the highest for all models, while in general they perform the worst on OD-pair 1. Furthermore, for all models the behavior in the first 10 runs t of a certain choice situation c are less well predicted than the last 10 runs t. This is in line with the expectations. With respect to the different driver types d all models perform best on driver type 2. This driver type exists of almost no switching choices. Almost all models perform the least on driver type 4, except the inertia model, which performs the worst on driver type 3. These are the driver types in which a lot of switches are made. Note that there is no model performance available for driver type 1, because this driver type was excluded from the dataset due to lack of experience on both route alternatives.

It can be seen that all developed regression models except the four choice strategies model perform better than the commonly used shortest path theory. Therewith these model approaches seem promising.

4.4   Conclusion

In order to identify important attributes related to inertia, six models are developed, each accounting for Inertia on a different level. Most of the attributes appear in more than one model (e.g. several personality traits, familiarity and travel time related issues and time of day, gender and education). The data-analysis (section 3.3) indicated that variables related to individuals and route characteristics might be important. The regression models are in line with this finding, as they all include several of these variables. From literature it was found that experiences by individuals on the route alternatives would be of influence. However, from the variables on experiences only the number of switches and

the percentage difference in experienced travel time are included in two of the models. Although, one could consider the travel time difference at run t-1, as included in the inertia model (and therewith the combined model), to be an 'experience' variable. Literature also suggested that travel time, travel speed, travel distance, familiarity and factors related to the simplicity of routes would be important. All regression models include a variable related to travel time, four models include a variable on familiarity and three models include a variable on travel speed. However, travel distance and variables related to route simplicity, such as difference in number of intersections, left turns, horizontal curves and merges and diverges, do not seem to be important in explaining any of the choice strategies as they are not included in any of the models. So, overall, the models that are found do not completely underline the findings in literature.

It is found that five out of six model approaches outperform the commonly used shortest path theory, which gives reason for continuation of this research in the chosen direction. The overall best performing explanatory model turned out to be the adapted four strategies model closely followed by the compromising model. However, as some parts of the adapted four choice strategies model might feel counter intuitive and application of the model is not quite straightforward, this model is considered to be not suitable for route choice predictions and is therefore excluded from further investigation. Due to the lower performances of the non-adapted four choice strategies model and the illogical model, these models are also excluded from further investigation.

Now, only the inertia model, compromising model and combined model are left to be considered. When the behavioral regression models are implemented in an actual route choice model, a model that covers all choice strategies, instead of only the inertial or compromising strategy, is expected to perform better. In fact, when for instance the inertial model is implemented in a route choice model, some assumptions need to be made on how to treat the cases in which inertial behavior is not possible. One might simply assume that the shortest route alternative is chosen. However, in that case the existence of a compromising strategy is totally neglected. The same applies to the compromising model, neglecting the existence of inertial behavior. Based on these considerations, it can be concluded that the combined model is the most suitable model for implementation in a route choice model and therefore will be used in the continuation of this research. The next chapter will elaborate on the modeling approach and introduce the modeling framework for the route choice model.

5 Modeling framework of route choice model

In chapter 4 the most important attributes related to inertial behavior and the indifference band (indirectly) are identified. These are obtained in the form of a regression model, which can be implemented in a model framework in order to extend the prediction from choice strategy to actual route choice. This chapter will elaborate on the approach that is best to use for the route choice model (section 5.1), which leads to a modeling framework for the route choice model (section 5.2). Subsequently, a different travel time updating process is suggested and examined (section 5.3). Lastly, the findings and results are assessed and conclusions are drawn (sections 5.4 and 5.5).

5.1 Model approach

The model approach that will be used as a starting point to develop an improved route choice model is based on the user equilibrium theory in which each driver non-cooperatively tries to minimize his travel cost (i.e. travel time) and chooses the shortest path. This is a simple and general applicable modeling approach that is widely used in route choice modeling. However, the user equilibrium theory is a static modeling approach. Within the context and objective of this research the model should focus on predicting the individual choices of travelers on a daily base. In other words, the model should be dynamic. From the theoretical framework it follows that learning is a fundamental issue in day-to-day route choice dynamics. Therefore, most state-of-the-art models include an updating process, updating the perceptions and expectations for the next run t+1. By replacing the shortest path for the shortest expected travel time path of individual i, which is updated after every trip, the modeling approach becomes dynamic, while it is still simple and general applicable. This dynamic expected shortest path approach will be the first step in the used model approach.

The obtained regression models might now be implemented in de model framework as a strategy module that determines if the route that is predicted by the dynamic shortest path approach (i.e. the shortest route based on expected travel times) is actually chosen or if the individual i finally chooses the other route alternative (i.e. the longer route) based on the predicted choice strategy (i.e. inertial choice versus non-inertial choice or compromising choice versus non-compromising choice). Depending on their attributes some updating process within the attributes might be necessary. This model framework will be illustrated in the next section.

5.2 Model representation

Based on the issues mentioned in the previous section the model framework shown in figure 14 is developed. As can be seen, it consists of a 2-step-model based on a Dynamic Expected Shortest Path Module and a Choice Strategy Module. First an initialization is necessary defining the input for the model which consists of individual characteristics and route characteristics, depending on the attributes that are used in the regression model, and the initial expected travel time at day t, which is determined based on the average travel times of the route alternatives. Subsequently, the Dynamic Shortest Path Module predicts the preliminary route choice that should be chosen based on the shortest expected travel time for day t by individual i in choice situation c. The Choice Strategy Module might alter this preliminary choice based on the choice strategy predicted by the regression model (i.e. combined model). This leads to a prediction of the final route choice of individual i on day t for choice situation c. Based on this predicted choice the expected travel times and number of switches are updated for the prediction of the route choice on day t+1 by the same individual i in the same choice situation c.
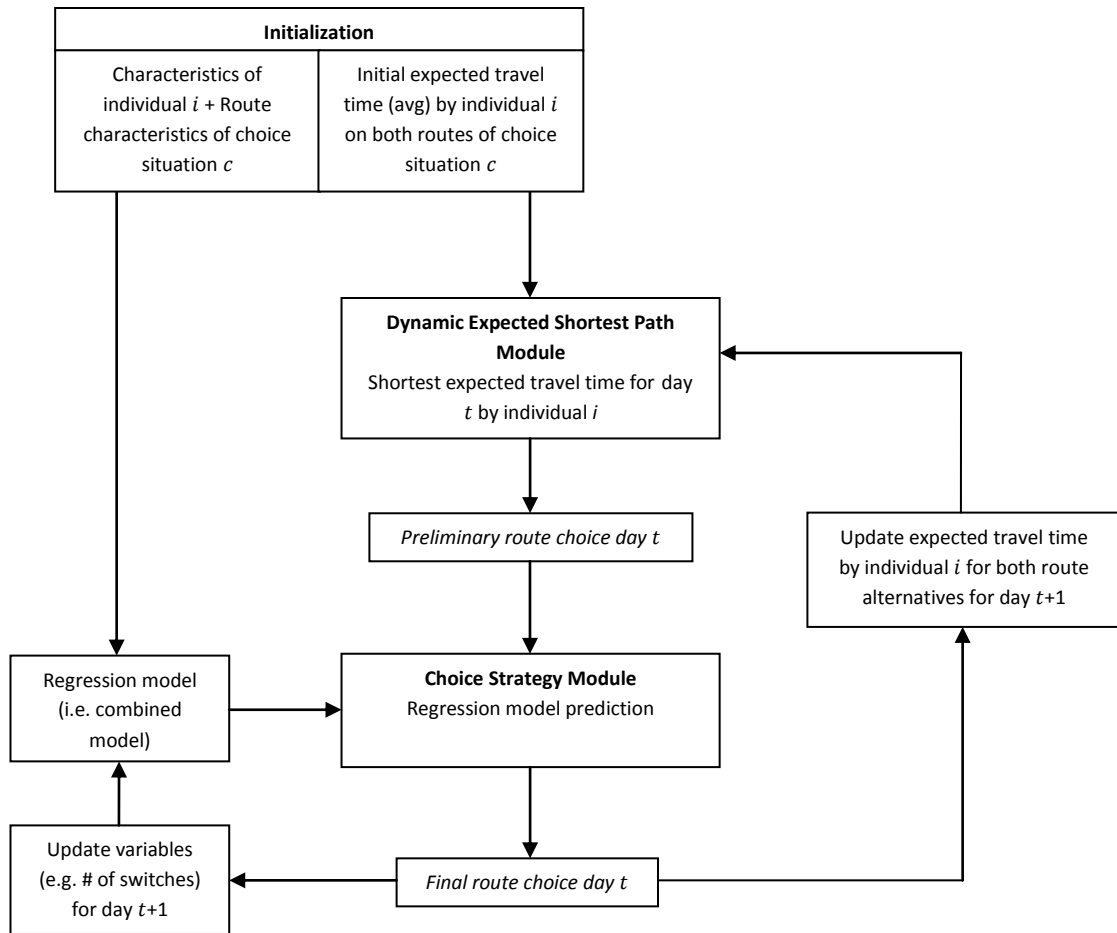
Figure 14: Developed model framework '2-step-model'

Note that this developed 2-step-model can only be used in cases with two route alternatives, since the variables in the regression models are based on the difference between the two route alternatives as used in the experiment of Tawfik. In order to make the model framework more general applicable a module should be added in order to downsize the number of considered route alternatives (i.e. choice set) before applying the model framework. However, this is outside the scope of this research as this research focuses on including inertial behavior and the indifference band in route choice modeling.

5.3 Updating process of expected travel time

As explained in chapter 4 the regression models identifying the important attributes are developed using an updating process of the expected travel time for the different route alternatives based on averaging the experienced travel time on all previous runs t experienced by a certain individual i. However, in that case it is assumed that all the experienced travel times have the same weight on the expectations of this individual i. It might be more realistic to assume different weights for the experienced travel times that are experienced at a time long ago and the experienced travel times of run t-1 in order to determine the expected travel time for run t. Therefore the influence of the experienced travel times at the previous runs are smoothed based on the following formula, which is vastly used, among others by Vaughn, Abdel-aty, Kitamura, Jovanis, and Yang (1993) and Mahmassani and Srinivasan (1995):

$$TT_{exp,t} = \alpha TT_{t-1} + (1 - \alpha)TT_{s,t-1} \qquad 0 \leq \alpha \leq 1$$

in which α is a smoothing factor whose value gives an indication of the relative importance of an individual i's previous experiences in updating his expectations on the current run t, TT_{t-1} is the experienced travel time at run t-1 and TT_s is the smoothened travel time, which is in fact the expected travel time at run t-1.

Note that the used choice strategy (i.e. if an inertial, minimizing (by switching or non-switching) or compromising choice is made) at each observation might change as a result of the new expected travel times at each smoothing factor. Therefore, the current combined model is fitted on the dataset with the (i.e. smoothened) expected travel times in order to find the smoothing factor α at which the performance of the current model would be the highest. A binary regression analysis method entering the important attributes is used.

5.4   Results and findings

Figure 15 shows the performance of the 2-step-model at different values for the smoothing factor α. It can be seen that at an α with a value of 0.01 the route choice model achieves the highest model performance, at which 74.49% of all cases is correctly predicted. Table 17 shows the model performances that the 2-step-model and the first step of the 2-step-model (i.e. the Dynamic Expected Shortest Path Module, which is referred to as the 1-step-model) obtained using the different updating processes. For both models the smoothing updating process results in the highest model performance (for the 2-step-model an increase of 5.5% point is obtained) and is therewith the best method to continue with in this research. Note that for the 1-step-model the highest model performance is obtained at a smoothing factor α of 0.4 and not at an α of 0.01 (see figure 16). The table shows that the second step of the 2-step-model is a valuable addition to the first step as the model performance increases with about 8.5% point.
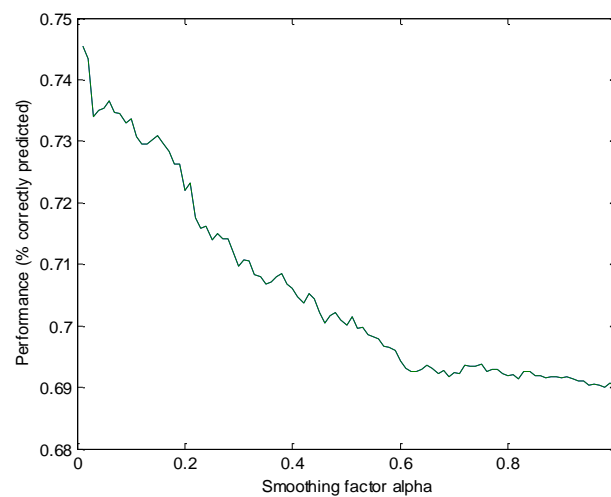
Figure 15: Performance of 2-step-model with combined approach at different values for α (step size is 0.01)

Table 17: Model performance in terms of % correctly predicted cases using different updating processes

Updating process	1-step-model	2-step-model
Averaging approach	65.13%	68.89%
Smoothing approach	66.05% (α=0.4)	74.49% (α=0.01)
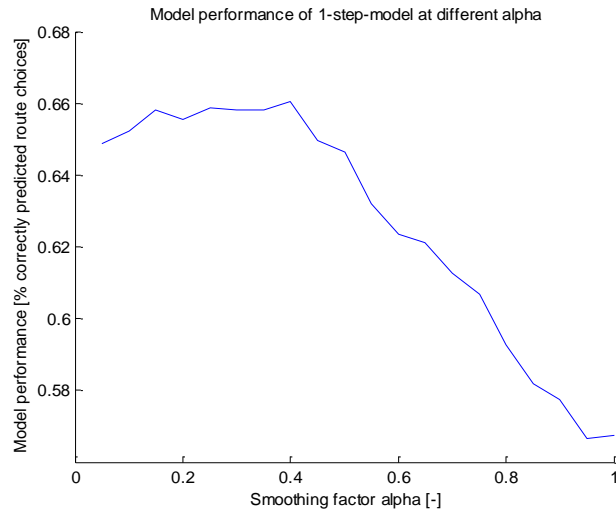
Figure 16: Performance of the 1-step-model at different values for α (step size is 0.05)

The optimal value found for α in the 2-step-model is very low, which indicates that the experienced travel time at run t-1 does not change the expectations of a certain individual i much. This means that the initial expected travel time by individual i is very important. Remember that in this 2-step-model the initial expected travel time is determined based on the average experienced travel time by all participants at the specific time of day individual i is making his choice.

Note that with a smoothing factor α of 0.01 the dataset for the analysis of the inertia model consists of 474 observations and the dataset for the analysis of the compromising model consists of 719 observations (see figure 17a). Furthermore, figure 17b shows that at a smoothing factor α of around 0.2 till 0.4 the inertia model performs the worst while the compromising model performs the best. At a smoothing factor α of 0.01, the performance of the inertia model is 70.36%. The performance of the compromising is a little higher at this α, 77.09%. Both the dataset size graph and performance graph show similar trends for the inertia model and the compromising model. This indicates that the performance is to some extend dependent on the dataset size. One can imagine that at a certain point a dataset can be too small to obtain an accurate model, while with a bigger dataset a higher accuracy can be obtained.
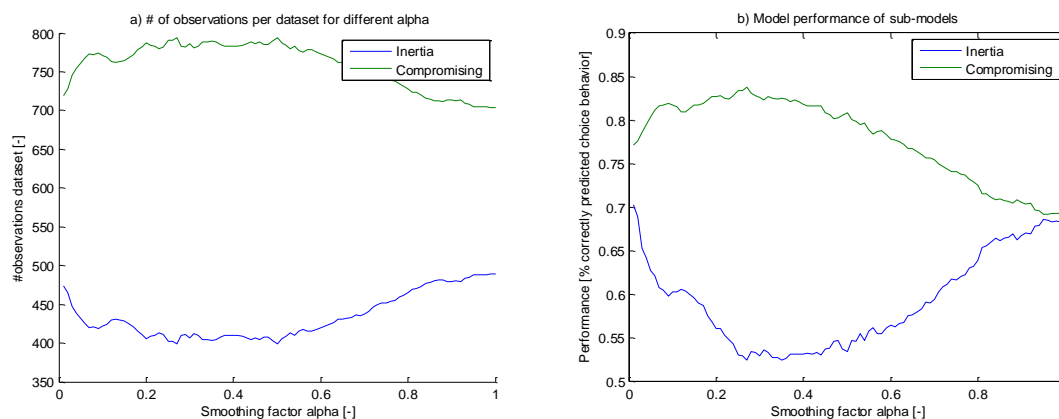
Figure 17: a) Number of observations and b) performance per dataset - for both sub-models at different values for α (step size is 0.01)

As mentioned before, the used choice strategy (i.e. if an inertial, minimizing (by switching or non-switching) or compromising choice is made) at each observation within the dataset might change as a result of the new expected travel times at each smoothing factor α. As a result, the model was fitted on each resulting dataset for the different smoothing factors. The model coefficients at which the best model performance (i.e. 74.49% correctly predicted cases) was obtained by the use of a smoothing factor α of 0.01 are shown in table 18.

One can imagine that as a result of the changed choice strategies being identified at each observation within the dataset, other attributes might turn out to explain these choice strategies better. Therefore, a stepwise binary regression analysis was performed on the dataset including the newly identified choice strategies. Unfortunately, no regression model could be found that would improve the current model performance.

Table 18: Regression models fitted on the new dataset with changed choice strategies at α=0.01

Model	Inertia model		Compromising model	
	Beta	Significance	Beta	Significance
Constant	3.705	0.020	-7.648	0.000
Time of day$_c$=0	Reference			
Time of day$_c$=1	3.148	0.000		
Time of day$_c$=2	1.818	0.000		
Ethnicity$_i$=0	Reference			
Ethnicity$_i$=1	1.854	0.199		
Education$_i$=0	Reference		Reference	
Education$_i$=1	-0.736	0.567	-0.567	0.125
Education$_i$=2	-2.249	0.150	-3.103	0.000
Education$_i$=3	-0.699	0.637	-2.057	0.000
Driving years$_i$	0.090	0.008		
C$_i$	-0.062	0.171	0.178	0.000
Maximum familiarity$_{ic}$	-0.328	0.034	-0.175	0.108
ΔTT_prev$_c$	-0.929	0.000		
Residency$_i$	-0.106	0.051		
Gender$_i$=0			Reference	
Gender$_i$=1			-1.039	0.003
E$_i$			0.108	0.000
ΔTTabs$_c$			-0.979	0.000

* Time of day$_c$, Ethnicity$_i$, Gender$_i$ and Education$_i$ are categorical variables. Each category in the model functions as a dummy variable. The category indicated with 'Reference' is the reference category (i.e. Beta=0).

Note that not all variables turn out to be significant anymore. This is the case for the variable 'Maximum familiarity$_{ic}$' in the compromising model and for the variables 'C$_i$', 'Education$_i$' and 'Ethnicity$_i$' in the inertia model. However, these variables have shown to be significant in explaining inertial behavior and compromising behavior before in chapter 4. Therefore, we do not exclude these variables from the models.

For the inertia model signs have changed for some values of the variables 'Time of day$_c$', 'Ethnicity$_i$' and 'Education$_i$' (compared to the coefficients found in chapter 4). For the compromising model the same happens for some values of the variables 'Gender$_i$' and 'Education$_i$'. Remark that sign changes only occur at the categorical variables in the sub-models. Reason for this might be that each category of these variables is valued related to their reference category. Small shifts in both the reference category and one of the other categories within a certain variable can easily cause the sign to switch. It is likely that these sign changes do not lead to illogical model behavior, as the behavior the coefficients represent still seem to be explainable.

5.5 Discussion and conclusion

This chapter has introduced a 2-step modeling framework consisting of a Dynamic Expected Shortest Path Module and a Choice Strategy Module. The first determines a preliminary choice based on a travel time updating process and the second alters this preliminary choice based on the predicted choice strategy by the combined regression model. It was found that an improvement in model performance of approximately 5.5% point can be achieved using a travel time updating method based on smoothing the experienced travel times. A very small smoothing factor α of 0.01 was found in order to obtain the best model results. This contradicts literature findings.

For example, Dion and Rakha (2003) used a smoothing factor α of 0.1 within their Transmit algorithm in order to estimate the expected link travel time on a certain day based on historical experiences. Yang, Kitamura, Jovanis, Vaughn, and Abdel-aty (1993) even found a much higher smoothing factor α of 0.8 to be optimal to use in their exploration of route choice behavior with advanced traveler information. Although these values found in literature are very distinct they both consider current experiences to be of higher importance than was found in this research. In addition, many researches found that more recent experiences are generally more important in route choice behavior (e.g. Bogers (2009) and Chen (2007)).

Despite indications that the used smoothing factor in this research is very low, it is quite logical when looking at the used dataset. From chapter 3.3 it is known that the complete dataset with 2065 observations consists for 56% of non-switching route choice patterns (i.e. driver type 1 and driver type 2) and driver type 3 might also contain a lot of non-switching choices because of the clear preference for one of the routes that defines this driver type. However, the used dataset consists of only 1193 observations out of these 2065 observations. As a result, about 40% of the data consists of non-switching behavior type 2, while an even higher percentage contains driver type 3. So in short, the used dataset does contain a lot of non-switching choices. One can imagine that those choices are consistent with the hypothesis that their expectations of the different route alternatives do not change much. This would, in fact, explain the low smoothing factor found in this research and therewith indicate some kind of habitual behavior or route preference within this dataset. This habitual behavior or route preference might be based on experiences that are gained by individuals before the experiment and can therefore not be found within the dataset. In addition, one can imagine that if for each driver type a smoothing factor α is determined, it is likely that these will differ from each other. After all, different driver types might make different use of their past experiences.

Because of the new updating method the sub-models of the combined approach needed to be fitted to the new dataset, resulting in new coefficients for the sub-models. As some attributes in the sub-models turned out to be not statistical significant anymore, the validity of the model might be questioned. Therefore the next section will elaborate on the validity of the model.

6 Model validation

In the previous chapters a route choice model is developed. This chapter will validate this model in order to see if the model is an accurate representation of reality. Section 6.1 introduces the cross-validation techniques and determines which method will be most suitable. Subsequently, section 6.2 shows the results when the validation is executed. Based on these results, the model is recalibrated and re-validated in section 6.3. Lastly, section 6.4 concludes this chapter by drawing conclusions.

6.1 Cross-validation method

In this research a cross-validation technique is used in order to validate the 2-step-model. Cross-validation is often used for assessing how the results of a statistical analysis generalize to an independent data-set and estimating how accurately a predictive model will perform in practice. There are several methods in order to perform a cross-validation. The simplest is the holdout method. This method partitions the dataset into two mutually exclusive subsets; a training set on which the model is calibrated and a testing set on which the model is tested. The drawback is that the dataset is not effectively used, as training is only performed on part of the data, and the results might be misleading in case of an 'unfortunate' split. Therefore, in the random sub-sampling method this holdout method is repeated several times randomly splitting the dataset. However, still not all data might used for training the model. Another method is K-fold cross-validation, in which the dataset is randomly split into k mutually exclusive subsets. K-1 subsets are used for training and the remaining subset is used for testing. This is repeated until every subset has been used for testing. Advantage is that all the observations are used for both training and testing, using the available data more effectively. The last method that is considered is the leave-one-out cross-validation method. This method is comparable to the k-fold method, however, the number of subsets k is chosen to be the total number of observations. In other words, one observation is left out of the training dataset in order to be used for testing. This is repeated until all observations have been used for testing once. (Gutierrez-Osuna, n.d.; Kohavi, 1995).

In this research the leave-one-out cross validation method is used because it makes effectively use of the available data, using all observations for both training and testing, and it is systematic.

6.2 Results

Figure 18 shows the cross-validation results for the coefficients of the compromising model. The cross-validation results for the inertia model can be found in figure 19. No significant outliers can be identified for the compromising model by eye. The values for the different coefficients are found to be quite constant over each iteration. However, a more differing trend is visible for the value of the constant. In contrary to the results of the compromising model, the results for the inertia model show an outstanding peak when observation 147 is left out of the training set. Another notable peak, which is less extreme, can be observed at iteration 397 where observation 397 is left out of the training set. This indicates that these observations are outliers which heavily influenced the value of the coefficients of the model.

Therefore it can be concluded that the compromising model with the current coefficients is a valid model for predicting compromising behavior. In contrary to the results of the compromising model, the results for the inertia model show an outstanding peak when observation 147 is left out of the training set. Another notable peak, which is less extreme, can be observed at iteration 397 where observation 397 is left out of the training set. This indicates that these observations are outliers

which heavily influenced the value of the coefficients of the model. Calibrating the model without these observations will result in a more valid model for predicting inertial behavior.
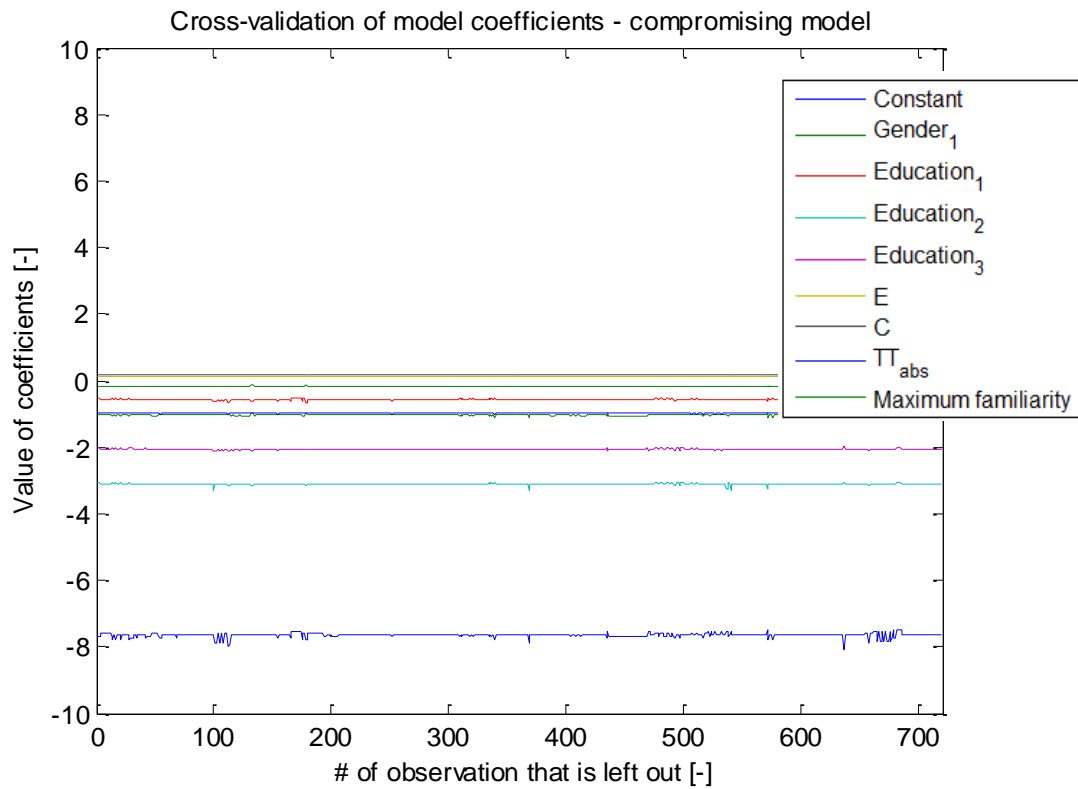
Figure 18: Results cross-validation of model coefficients - Compromising Model
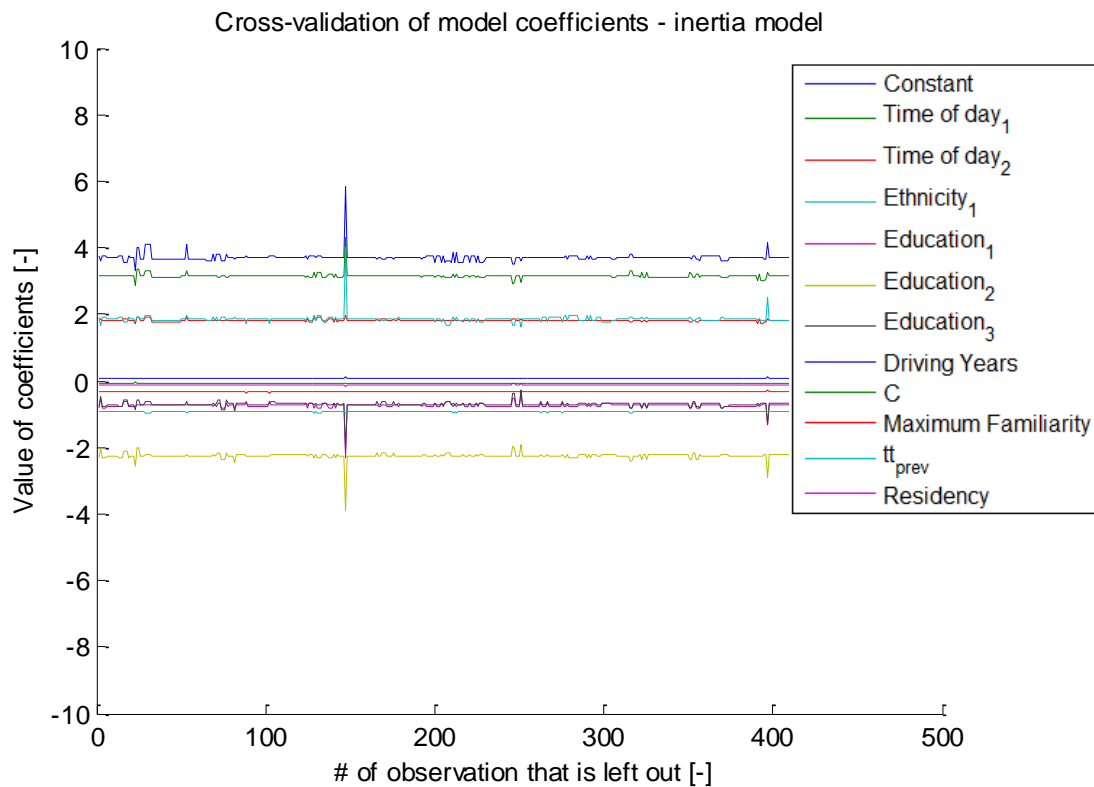
Figure 19: Results cross-validation of model coefficients - Inertia Model

In order to determine if an observation can be marked as an outlier in a more scientific way, the iterations at which the coefficient values deviate more than 3 standard deviations from the coefficient mean for 5 or more coefficients of the sub-model are identified. Figure 20 shows that, according the aforementioned outlier definition, for the inertia model 3 outliers can be identified (0.6% of model observations) while for the compromising model 7 outliers (1.0% of model observations) are found. This concerns observations 23, 147 and 397 for the inertia model and observations 112, 132, 133, 339, 368, 371 and 636 for the compromising model.
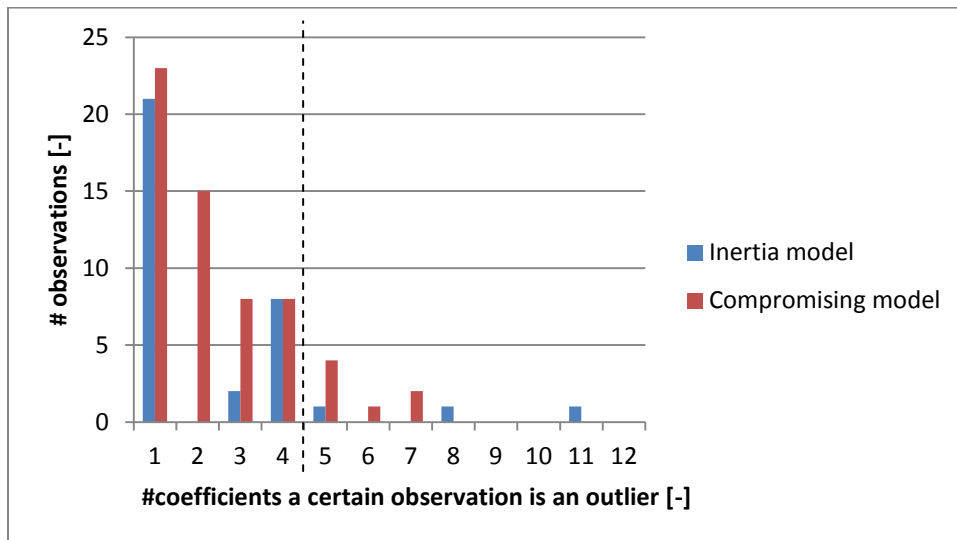
Figure 20: Identifying observations being outliers.

6.3 Re-calibrating and re-validating

Based on the results of the validation process both the inertia model and the compromising model are re-calibrated. In order to do this, first the outliers as identified in the previous section are excluded from the dataset. Subsequently, the new coefficients are defined using regression analysis by entering the current attributes. The new sub-models are shown in table 19.

Table 19: Inertia model and compromising model fitted on dataset without outliers

Model	Inertia model		Compromising model	
	Beta	Significance	Beta	Significance
Constant	6.342	0.000	-8.794	0.000
$Gender_i=0$			Reference	
$Gender_i=1$			-1.236	0.001
Time of $day_c=0$	Reference			
Time of $day_c=1$	4.3183	0.000		
Time of $day_c=2$	1.969	0.000		
$Ethnicity_i=0$	Reference			
$Ethnicity_i=1$	5.012	0.002		
$Education_i=0$	Reference		Reference	
$Education_i=1$	-3.333	0.019	-0.550	0.141
$Education_i=2$	-5.300	0.003	-3.354	0.000
$Education_i=3$	-3.226	0.042	-2.205	0.000
Driving $years_i$	0.153	0.000		
E_i			0.126	0.000
C_i	-0.078	0.082	0.200	0.000
Maximum $familiarity_{ic}$	-0.281	0.046	-0.196	0.075
ΔTT_prev_c	-0.998	0.000		
ΔTT_abs_c			-1.040	0.000
$Residency_i$	-0.214	0.000		

* Time of day_c, $Ethnicity_i$, $Gender_i$ and $Education_i$ are categorical variables. Each category in the model functions as a dummy variable. The category indicated with 'Reference' is the reference category (i.e. Beta=0).

In the previous chapter it was found that one attribute of the compromising model and three of the attributes in the inertia model turned out to be insignificant. Note that after re-calibration, for the compromising model the variable 'Maximum familiarity$_{ic}$' remains insignificant, while for the inertia model only the variable 'C$_i$' turns out to be insignificant. One should remember that these variables have shown to be significant in explaining inertial behavior and compromising behavior before (see chapter 4. Furthermore, the sign of none of the coefficients changes compared to the model obtained in chapter 5.

The cross-validation results of this model are found in figure 21 and figure 22. These validation results do not show any extreme peak values for the coefficients. This means that the model is quite robust. Therefore, it can be concluded that the coefficients of the re-calibrated sub-models are valid for predicting inertial and compromising choice behavior. Using these new coefficients the performance of the combined model increases slightly from 74.49% to 75.35%.
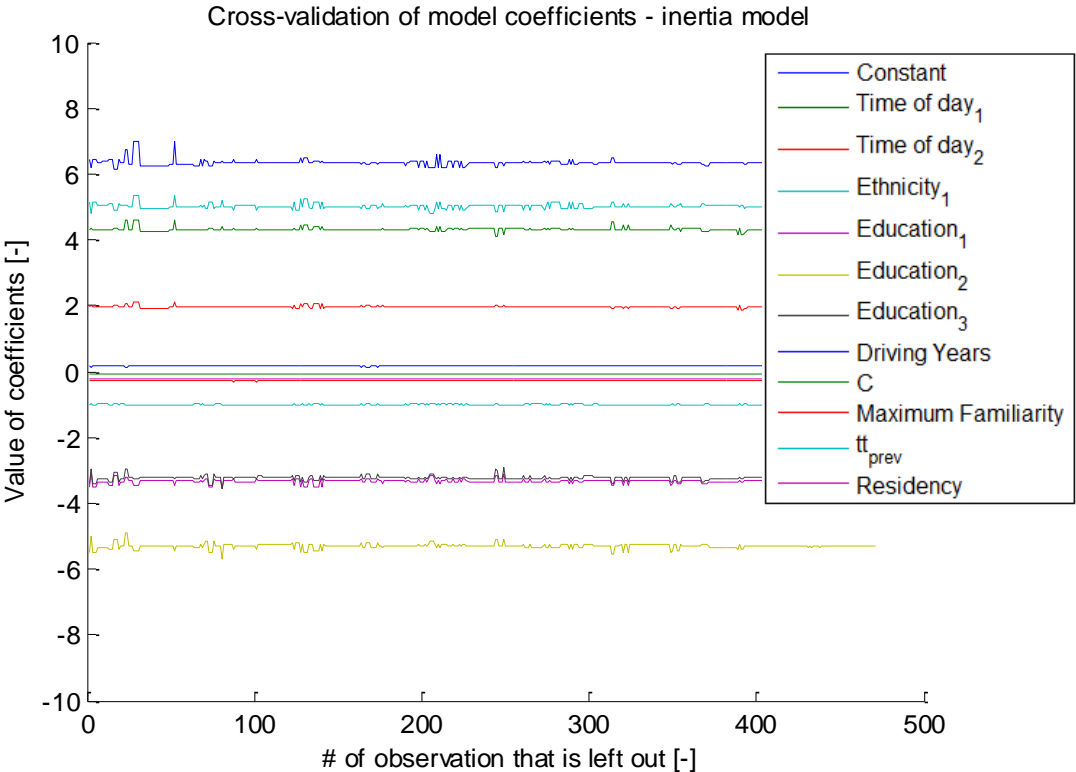
Figure 21: Results cross-validation of model coefficients after re-calibration - Inertia Model
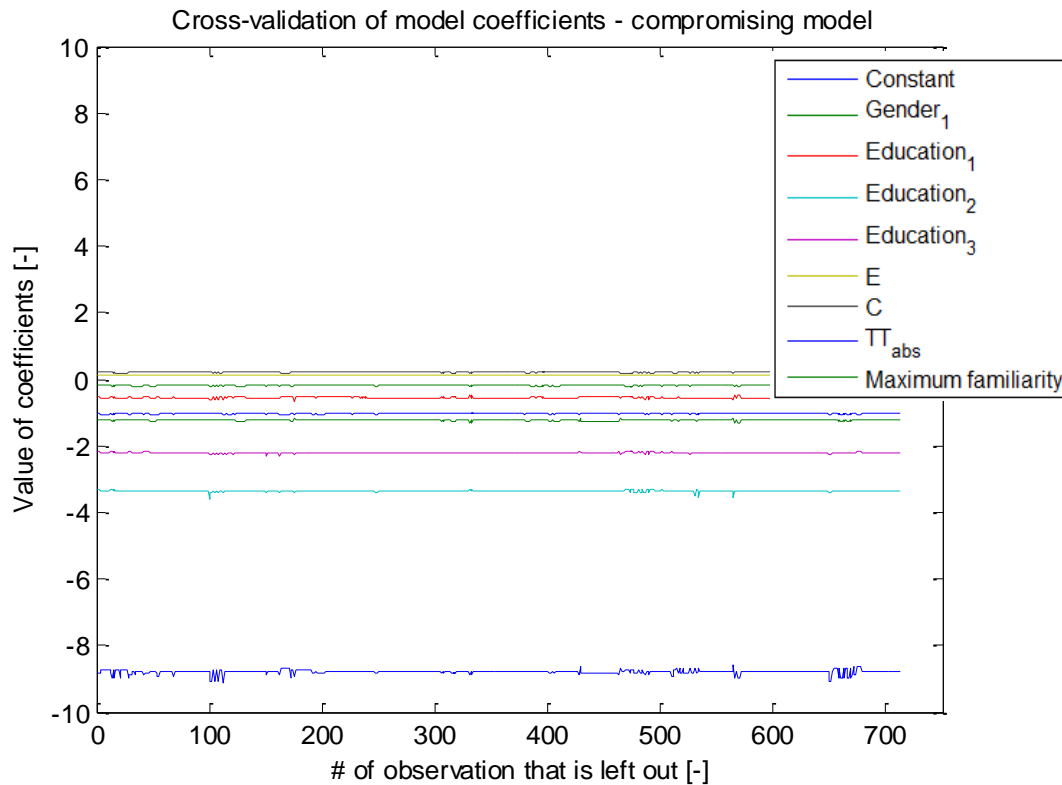
Figure 22: Results cross-validation of model coefficients after re-calibration - Compromising Model

Figure 23 and figure 24 show the performance of the sub-models on the observation that was left out of the dataset for training that model (i.e. testing part of the cross-validation method). In other words, it shows the model performance for each observation using the model coefficients that are calibrated without this specific observation. For example, when observation 1 of the sub-dataset on compromising is left out from training the compromising sub-model, the model using the in that case obtained model coefficients will provide a correct prediction on this observation 1 with a probability of 15%. This is done for each observation in the dataset. There is a significant variability in model performance noticeable for both models. The average testing performance of the compromising model is 69.27% and the average testing performance of the inertia model is 68.98%. Note that for the inertia model this is only 1% point lower as the performance of the inertia model found in chapter 5 (i.e. model performance of the inertia sub-model was 70.36%), while for the compromising model it is 8% point (i.e. model performance of the compromising sub-model was 77.09%). The average testing performance of the combined model is 69.15% with a standard deviation of 35.70. This seems to be a high value for the standard deviation. However, figure 23 and figure 24 do show high fluctuations varying from 0% to 100% which explains this high value.
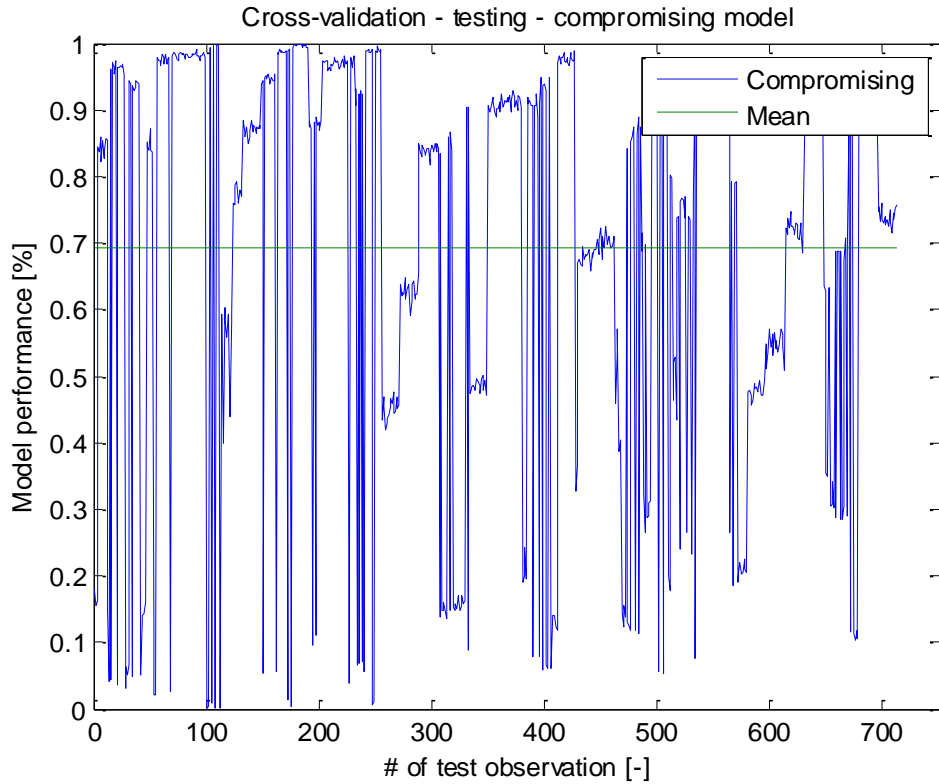
Figure 23: Testing of sub-model on each observation – Compromising Model
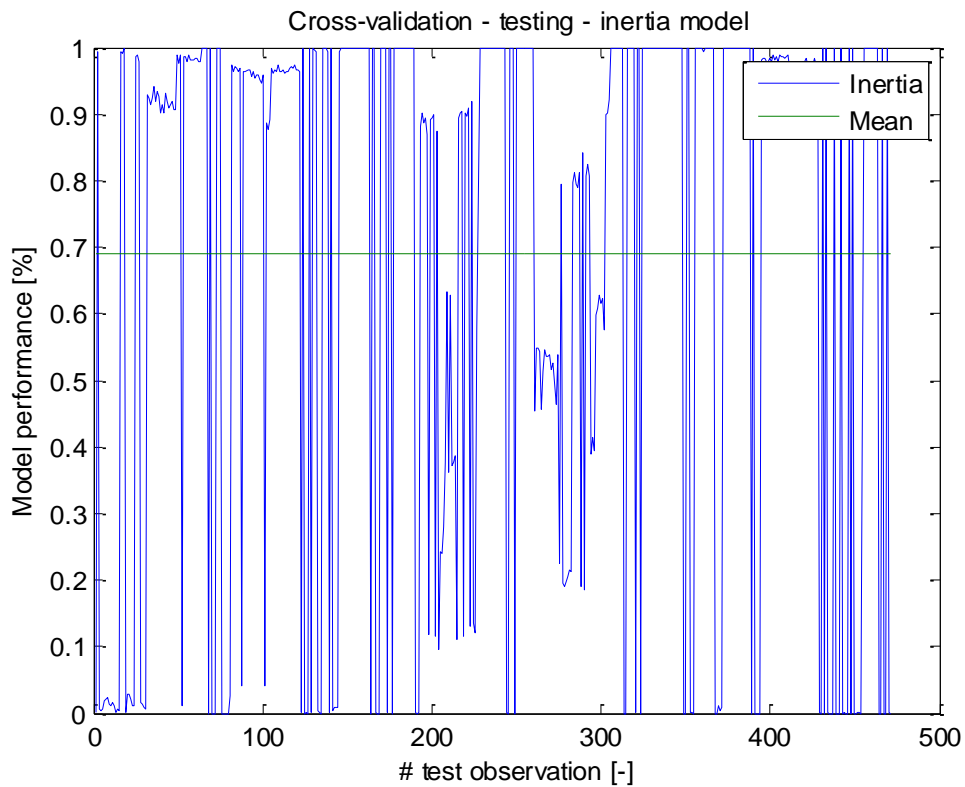
Figure 24: Testing of sub-model on each observation - Inertia Model

6.4 Conclusion

Both the inertia model and compromising model are tested on validity in predicting certain choice behavior using the cross-validation principle of leave-one-out in which one of the observations is left out of the training dataset in order to be used for testing. After identifying outliers and re-calibration of both sub-models on data without these outliers, it can be concluded that there are no considerable fluctuations within the model coefficients when calibrated on different parts of the dataset. Therefore, both models can be considered valid and it is justified to use them within the route choice model. The next chapter will now introduce heterogeneity to the 2-step-model using an agent-based approach.

7 Introducing heterogeneity using an agent-based approach

Currently the developed 2-step-model can only predict the route choices of the individuals of which the attribute values are known, assuming that they are homogeneous. In reality, however, populations are heterogeneous. A heterogeneous population can be simulated based on the homogeneous population sample that was used in developing the 2-step-model, assuming that this population sample represents average individuals from the total population. More precise, a population can be simulated by assuming the model coefficients β to be stochastic instead of deterministic. In other words, every simulated individual i has his own set of coefficients β, which are drawn from some distribution that is based on the population sample. This is called the agent-based modeling approach.

In section 7.1 samples drawn from the estimated parameter distributions will be obtained using different sampling methods. Subsequently, section 7.2 will elaborate on how to generate the sets of coefficients β from these distribution samples using the Cholesky Decomposition tool in order to simulate each individual i from the population. Then, these sets of coefficients are applied on the dataset in section 7.3 showing the resulting model performance. Finally, this chapter provides a conclusion and discussion on the found results in section 7.4.

7.1 Obtaining samples from parameter distributions

In this section parameter distribution samples are obtained using two different methods; Bayesian sampling and the Jack-knife approach. These methods are now elaborated upon.

7.1.1 Bayesian sampling

The Bayesian approach uses both prior information (i.e. what is expected or believed) and posterior information obtained by data collection according to the following conditional probability formula (Bolstad, 2007):

$$P(\theta|Data) = \frac{P(Data|\theta)\,P(\theta)}{P(Data)}$$

Where θ is the unknown parameter, $P(\theta|Data)$ is the posterior distribution, $P(Data|\theta)$ is the sampling density of the data (i.e. likelihood), $P(\theta)$ is the prior distribution and $P(Data)$ is the distribution of the present data (i.e. normalizing constant).

For most problems the posterior distributions are difficult or impossible to compute in an analytical way. Generalized linear models, such as the binary logistic regression model used in this research, are one of those (MathWorks, 2014). Luckily, Bayesian estimates of the model parameters can be obtained from their posterior distributions using the Markov Chain Monte Carlo (MCMC) slice algorithm as implemented in the Matlab software, which generates random samples from distributions based on the initial value of the sampling sequence (i.e. the initial model coefficients as provided in chapter 6), a prior distribution (i.e. assumed to be $N(0,100)$, which means no prior information is known) and the sampling density of the data (i.e. likelihood, assumed to be $B(1, P_{ct})$, where P_{ct} is the probability of certain choice behavior (i.e. inertial choice or compromising choice) to occur at each run t of all choice situations c).

The MCMC slice algorithm does not generate independent simulated distribution samples. Instead, each simulated sample depends on its immediate predecessor. That is, for each current simulated solution the algorithm evaluates a solution within the neighborhood space (which is set to 10 in

Matlab by default). Based on the probability of occurrence within the posterior distribution, this neighbor is adopted as the next simulation. In the end, each solution will be represented within the simulations according to its number of occurrence within the posterior distribution.

As a result of this dependency between each subsequent simulation, it might take a while before the effect of the initial values of the sampling sequence disappears and the Markov Chain reaches a stationary state. Therefore, the first distribution samples (i.e. 350 for the inertia model and 250 for the compromising model; these are called burn-in rates) are not used. Then, a total of 1000 distribution samples are obtained for the inertia model, while for the compromising model 500 distribution samples are sufficient. In order to obtain independent samples, these simulated samples are selected by picking only 1 simulated sample out of every 2000 simulations for the inertia model and only 1 simulated sample out of every 1500 simulations for the compromising model (these are called the thinning-rates). This prevents obtaining distribution samples that are close to each other in the Markov Chain and therefore being dependent on each other. Appendix C elaborates on how these values are set.

Based on the obtained distribution samples the posterior distributions are approximated by cumulative distribution functions. These approximate posterior distributions are shown in figure 25. The posterior distributions of some of the coefficients have wide dispersions, while others have not. This represents the heterogeneity of the population to these attributes as derived from the used dataset. A small dispersion indicates that there is high homogeneity to the extent that a specific attribute affects the choices of each individual i within the population, while a wide dispersion indicates that individuals weigh that attribute quite differently from each other. So apparently, the population is homogeneous in weighting personality traits, driving years, travel time and familiarity, while they are more heterogeneous in weighting the time of day, ethnicity, gender, education and their preference to expose a certain choice strategy as is caught in the model constants.
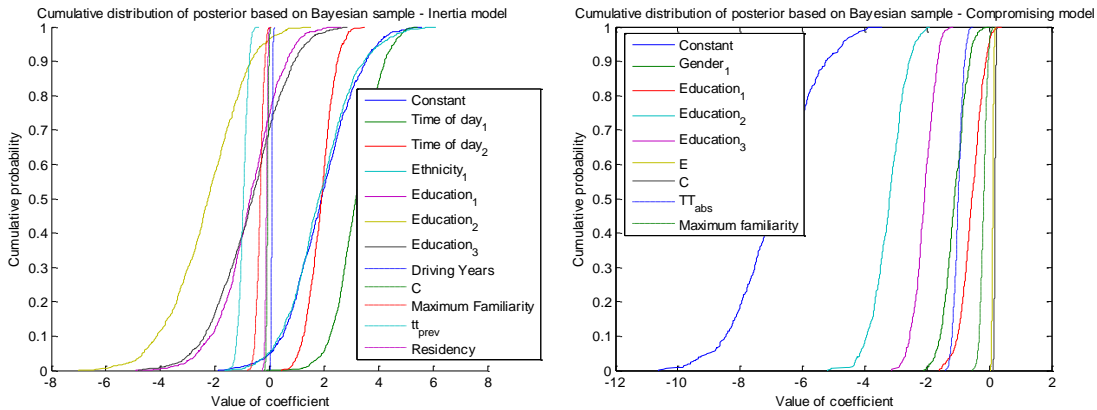

Figure 25: Approximate posterior distributions of the coefficients of a) the inertia model and b) the compromising model

7.1.2 Jack-knife approach

The jack-knife approach is used for model validation earlier in this report (chapter 6). The basic idea is that one of the observations within the dataset is left out of the data on which the model parameters are estimated using binomial regression analysis. This is repeated until all observations are left out once. In the end, some sample of the parameter distributions is obtained by all estimated parameters together.

7.1.3 Jack-knife versus Bayesian sampling

The main difference between the two sampling approaches is that the Jack-knife approach does not provide simulated samples and its sample size is therefore restricted to the number of observations within the dataset, while the Bayesian approach can provide an indefinite amount of samples. As a result, the jack-knife sample might not be large enough to be a correct representation of the underlying parameter distributions, while the Bayesian sample can simply be increased in order to obtain a representative sample. This implies that the Bayesian approach is more flexible to use. However, in this report both approaches are tested.

7.2 Generation of parameter replications

Now sets of model parameters β need to be generated by picking them out of the Jack-knife or Bayesian samples in order to simulate each individual i of the population. As some of the parameters might be correlated, picking these parameter replications independently might affect the model results significantly. Therefore, the parameter replications will be generated with and without accounting for these parameter correlations. Amer, Rakha, and El-Shawarby (2011) propose two approaches to generate sets of parameter replications accounting for correlation; Cascaded Regression and Cholesky Decomposition. The Cascaded Regression uses a regression analysis to cascade the model coefficients on each other in order to account for the correlations between the parameters. The Cholesky Decomposition is a matrix calculus tool that can be used to break a symmetric positive-definite matrix into the product of a lower triangular matrix and its conjugate transpose, which will be applied to a variance matrix accounting for the correlations between the parameters. The Cholesky Decomposition is chosen, as this approach is considered to be straightforward and more efficient.

The Cholesky Decomposition approach can be used to generate the parameter replications β given the following formula (Amer et al., 2011):

$$
\begin{array}{ll}
\mu_{\beta_0} + c_{00}Z_0 & = \beta_0 \\
\mu_{\beta_1} + c_{10}Z_0 + c_{11}Z_1 & = \beta_1 \\
\quad\vdots & \quad\vdots \\
\mu_{\beta_n} + c_{n0}Z_0 + c_{n1}Z_1 + \cdots + c_{nn}Z_n & = \beta_n
\end{array} \Rightarrow
$$

$$
\underbrace{\begin{pmatrix} \mu_{\beta_0} \\ \mu_{\beta_1} \\ \vdots \\ \mu_{\beta_n} \end{pmatrix}}_{\mu} + \underbrace{\begin{pmatrix} c_{00} & 0 & 0 & 0 \\ c_{10} & c_{11} & 0 & 0 \\ \vdots & & \ddots & 0 \\ c_{n0} & c_{n1} & \ldots & c_{nn} \end{pmatrix}}_{C} \underbrace{\begin{pmatrix} Z_0 \\ Z_1 \\ \vdots \\ Z_n \end{pmatrix}}_{Z} = \underbrace{\begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_n \end{pmatrix}}_{\beta}
$$

where μ is a vector containing the means of the distribution samples that are generated for the different coefficients β, Z is a vector containing random independent and identically distributed variables that are assumed to be normally distributed (i.e. $Z_n \sim N(0,1)$) and C is a lower triangle matrix that can be calculated using the Cholesky Decomposition tool.

Given that μ is constant and Z is standard normally distributed, the following holds (Amer et al., 2011):

$$Var(\mu) = 0, Var(CZ) = C\,Var(Z)\,C^T, Var(Z) = 1 \Rightarrow Var(\mu + CZ) = CC^T$$

Therefore,

$$Var(\beta) = \begin{pmatrix} \sigma_{\beta_0}^2 & & \rho_{ij}\sqrt{\sigma_{\beta_i}^2 \sigma_{\beta_j}^2} \\ & \ddots & \\ & & \ddots \\ \rho_{ij}\sqrt{\sigma_{\beta_i}^2 \sigma_{\beta_j}^2} & & \sigma_{\beta_n}^2 \end{pmatrix} = CC^T$$

This shown matrix can be easily calculated given the standard deviations of the coefficient distributions σ_β and the correlations between the parameters ρ_{ij}, which are determined according to the following formula (Amer et al., 2011):

$$\left.\begin{array}{c} \beta_0 \sim N(\mu_{\beta_0}, \sigma_{\beta_0}) \\ \vdots \\ \beta_n \sim N(\mu_{\beta_n}, \sigma_{\beta_n}) \end{array}\right| \quad \rho_{ij} = corr(\beta_i, \beta_i) \quad \forall i \neq j$$

Now Cholesky Decomposition can be used in order to break the obtained matrix into C and C^T and the formula $\mu + CZ = \beta$ can be solved in order to obtain the parameter replications β.

These parameter replications are obtained for both sub-models separately, so in fact, each simulated individual i gets two sets of parameters β; one for the inertia model and one for the compromising model.

The coefficients β without taking parameter correlations into account are calculated according to the following formula: $\mu + Z = \beta$, leaving the lower triangle matrix C out of the equation and assuming Z is normally distributed. Therefore, no Cholesky Decomposition is necessary to generate these coefficient sets.

7.2.1 Kolmogorov-Smirnov goodness-of-fit test

Note that $Z_n \sim N(0,1)$ assumes that the coefficients β are normally distributed. The distributions of the generated parameter replications β are therefore tested using the Kolmogorov-Smirnov goodness-of-fit test.

The Kolmogorov-Smirnov goodness-of-fit test (k-s test) is a test that can be used to compare a sample with a reference probability distribution (one-sample k-s test). The Kolmogorov-Smirnov statistic quantifies the difference between the empirical distribution of the sample and the reference distribution. The maximum absolute difference is used as test statistic, based on which the hypothesis that the sample distribution is equal to the reference distribution. As the Cholesky Decomposition tool assumes the coefficients to be normally distributed, the reference distribution is set to a normal distribution. A significance level of 0.05 is used.

For the Bayesian parameter replications, no evidence was found to reject the hypothesis that the obtained parameter distributions are normally distributed at a significance level of 0.05. However, for the Jack-knife parameter replications a normally distributed distribution was rejected for all variables in the sub-models. This is likely to be the case because the Jack-knife estimates are directly dependent on the used dataset instead of being simulations. Therefore, its distribution will follow the observations closely and the distribution underlying these observations will not be reached. The use of the vector Z for picking parameter sets out of the Jack-knife estimates is therefore not justified. There exist other methods that might be useful in this case (e.g. Cascaded Regression). However, these are not considered within this research and therefore no further examination is conducted on this Jack-knife approach.

7.3   Model application and results

A 1000 individuals are simulated using the Bayesian approach and Jack-knife approach, both in combination with the Cholesky Decomposition tool in order to create sets of parameter replications β accounting for correlations among the parameter values. In other words, 1000 sets of parameter replications β are obtained. Now the agent-based 2-step-model is applied on the available data observations using the 1000 different parameter sets on each of the 1193 observations within the available dataset. This represents the predicted choice of each individual i out of the population of 1000 individuals in that certain situation as represented by the specific observation.

The performances of the Bayesian model approach with and without considering parameter correlations are shown in table 20, broken down by sub-model as well as showing the combined result. Each is detailed per OD-pair pq and per 10 runs. For comparison, the performance of the initial 2-step-model is also included.

Table 20: Agent-based model performances using Bayesian approach (parameter correlations vs. no correlations)

Correctly predicted route choices	Bayesian inertia model		Bayesian compromising model		Bayesian combined model			Initial 2-step-model
	No correlations	Correlations	No correlations	Correlations	No correlations	Correlations		
OD-1 [%]	50.38	71.71	50.53	58.53	50.43	66.69		67.26
OD-2 [%]	50.60	66.99	52.05	79.80	51.54	75.26		76.37
OD-3 [%]	50.89	64.51	52.44	82.36	52.04	77.73		78.67
OD-4 [%]	51.20	76.40	50.71	61.52	51.03	71.30		71.75
OD-5 [%]	51.77	68.35	52.58	83.96	52.46	81.60		82.33
First 10 runs [%]	44.26	59.83	45.05	65.30	44.72	62.97		63.40
Last 10 runs [%]	56.45	79.74	56.89	85.67	56.72	83.43		84.52
Driver type 1 [%]	-	-	-	-	-	-		-
Driver type 2 [%]	51.32	84.06	53.10	90.75	52.58	88.78		89.98
Driver type 3 [%]	50.62	66.94	50.97	65.92	50.80	66.42		66.92
Driver type 4 [%]	50.21	50.54	50.22	54.50	50.21	52.79		53.13
Total correctly predicted [%]	50.79	70.50	51.98	77.22	51.51	74.55		75.35

It can be seen from table 20 that the results found for the Bayesian combined model accounting for correlations follow quite the same trend as the results obtained with the initial 2-step-model. However, its overall performance is slightly lower, although on OD-pair 2 and OD-pair 3 slightly higher performances are achieved. This might be due to the randomness in generating the parameter replications. Furthermore, note that the performances found for the Bayesian models ignoring correlations have a value of around 50%. As earlier mentioned (section 9.4), predicting route choices by choosing them randomly (i.e. each route alternative has an equal probability to be chosen) results

in about 50% of the route choices being correctly predicted on average. This indicates that ignoring the parameter correlations within a route choice model is comparable to predicting route choices randomly. This finding feels intuitive as the generation of the parameter replications only depends on the value of the random variable Z. One can imagine that random parameter values result in random choice prediction.

7.4 Discussion and conclusion

This chapter introduced an agent-based approach of the 2-step-model. Depending on the fact if parameter correlations within the model are captured or ignored, significant differences in model performances are obtained. This is in line with the findings of Kim and Mahmassani (2011) who examined the effect of correlated parameters in driving behavior models on car-following and found significant differences in their output measures as well.

In this research it is found that an agent-based approach ignoring parameter correlations has no added value compared to a random prediction process. However, accounting for parameter correlations increases the performance of the agent-based model by approximately 25% point, emphasizing the importance of these parameter correlations. Based on this, it follows that in route choice behavior the different combinations of attribute values affect the final route choice that is made by an individual i. Remember from chapter 4 that most variables are individual-specific. Therefore, a reality alike representation of the composition of the population within a certain area might be crucial in predicting route choices on a road network within this area, in order to obtain useful and accurate predictions.

Overall, the agent-based 2-step-model based on Bayesian simulations provide similar results as the general 2-step-model and therefore this might be a good method to apply the developed model within micro-simulation studies; it makes the model more flexible and easier transferable to other choice situations and demographics. Because of the similar results this approach has potential, although for the purpose of this research it has no added value. Therefore, the general 2-step-model is used in the continuation of this research. The next chapter will assess the sensitivity and robustness of the general 2-step-model.

8 Robustness and sensitivity analysis

A new route choice model is developed. For new models, it is not easy to comprehend its working. In order to obtain insights in the working of the model, the relationships between input and output variables in the model are identified in a sensitivity analysis. In addition, this will provide insights on the robustness of the model. In section 8.1 the actual analysis will be conducted and in section 8.2 the findings will be discussed and conclusions will be drawn.

8.1 Method, results and findings

One of the most common and simple approaches used in performing a sensitivity analysis is that of changing one factor at a time, keeping others at their original values. The influence of a certain factor j on the model output is represented by the coefficient β_j. Therefore, in order to change factor j the value of the coefficient β_j is changed using different percentages of the original value (i.e. ranging from -50% till +50% of the original value with a step size of 10%). The model performance using these different percentages reveals the effect of this specific factor on the model output. Figure 26 till figure 38 show the results for each attribute x_j and the constants used in the combined model. In order to make comparisons more easily, the scale of the axis of the model performance [%] is the same in all graphs. Note that some of the attributes only occur in one of the sub-models of the route choice model. As the number of observations on which a certain sub-model is applied differs, the sensitivity of the route choice model may be affected by this.
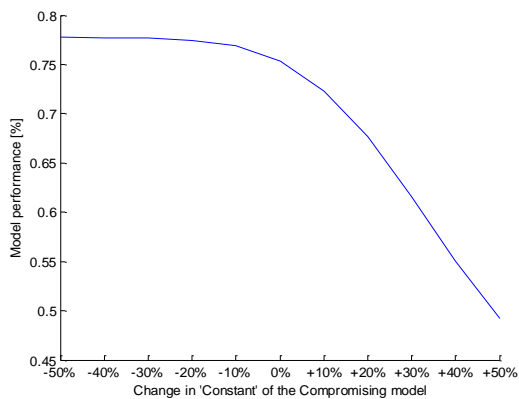
Figure 26: Model sensitivity to 'Constant Compromising'
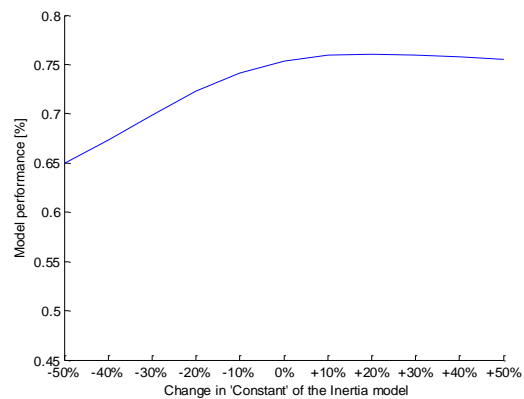
Figure 27: Model sensitivity to 'Constant Inertia'
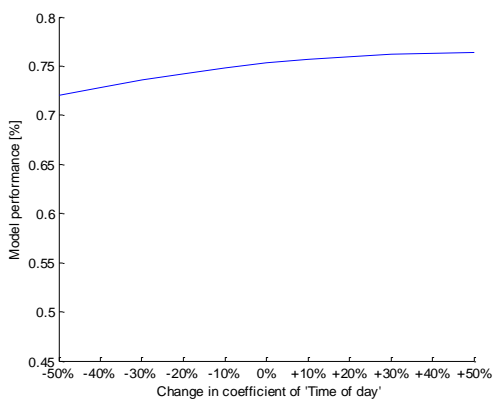
Figure 28: Model sensitivity to 'Time of day'.
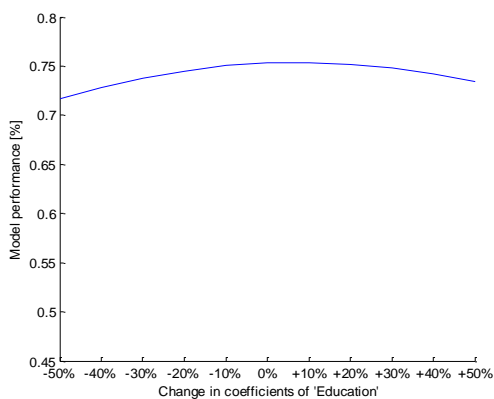
Figure 29: Model sensitivity to 'Education'
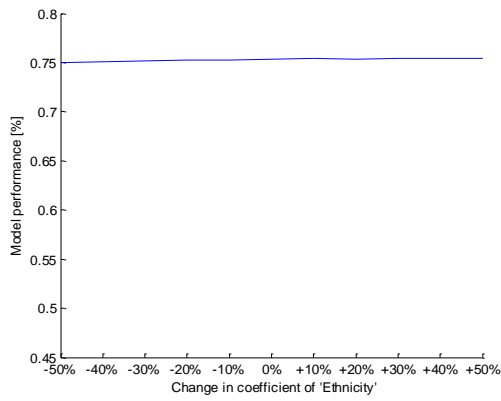
Figure 30: Model sensitivity to 'Ethnicity'
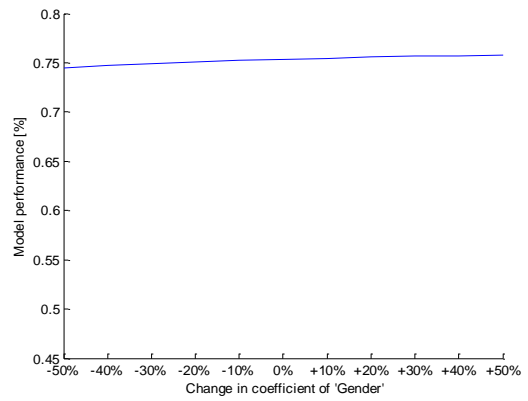
Figure 31: Model sensitivity to 'Gender'
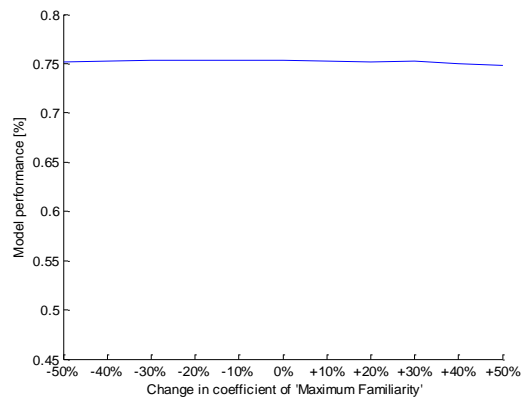
Figure 32: Model sensitivity to 'Maximum Familiarity'
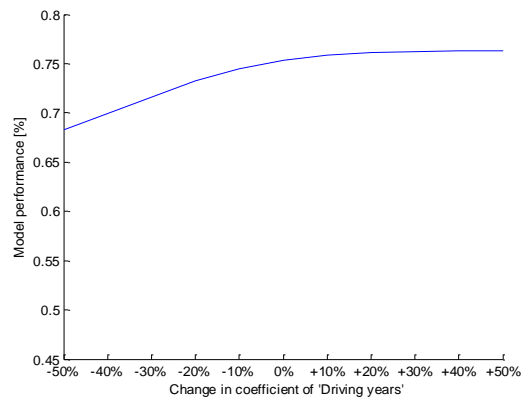
Figure 33: Model sensitivity to 'Driving years'
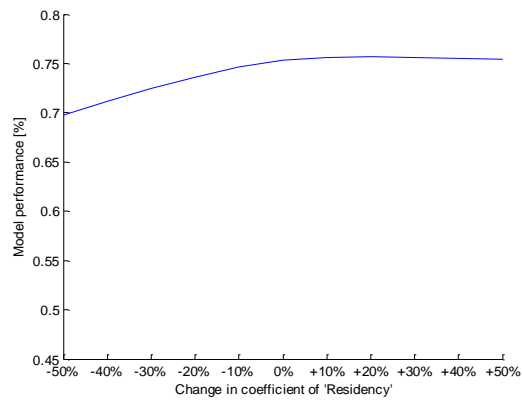
Figure 34: Model sensitivity to 'Residency'
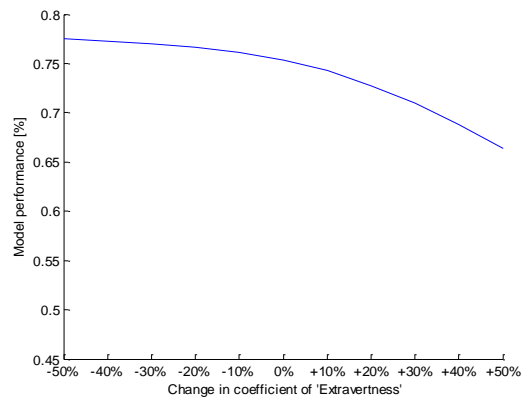
Figure 35: Model sensitivity to 'Extravertness'
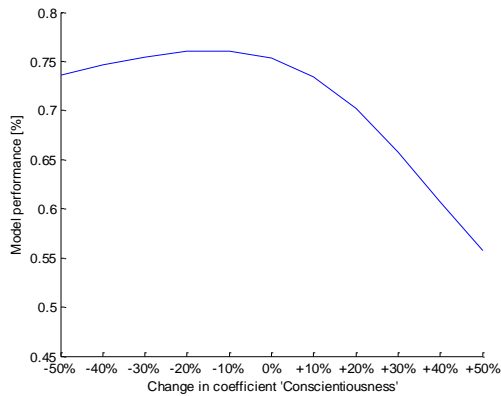
Figure 36: Model sensitivity to 'Conscientiousness'
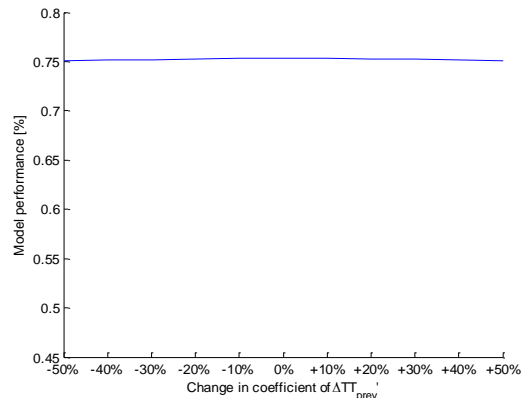
Figure 37: Model sensitivity to 'Δtt_{prev}'
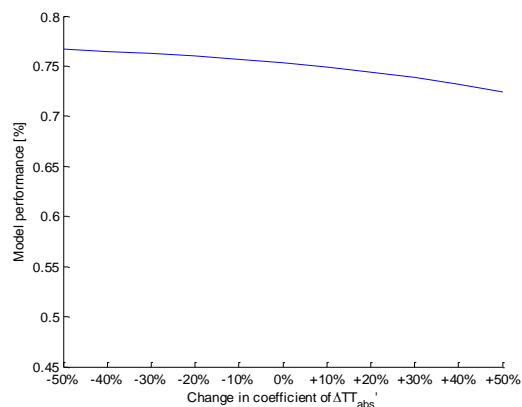
Figure 38: Model sensitivity to 'Δtt_{abs}'

Figure 26 and figure 27 illustrates the sensitivity of the model to the constants of both sub-models. It can be seen that the model is highly sensitive to the constant of the compromising model and to a lesser extent sensitive to the constant of the inertia model. This is as expected, as the compromising sub-model is applied more often (on 719 out of 1193 observations) than the inertia sub-model within the combined model. The model constant indicates if in general an individual i would be more likely to expose one of the two possible choice strategies (i.e. minimizing or compromising/inertia) in the absence of any of the included attributes. In other words, it represents a general preference for the exposure of a certain choice strategy. As the original values for de constants are -8.79 for the compromising sub-model and 6.34 for the inertia sub-model, it follows from the figures that the model performance decreases as the value of these constants is closer to '0'. This can be explained by the basic working of the sub-models, illustrated in figure 39.
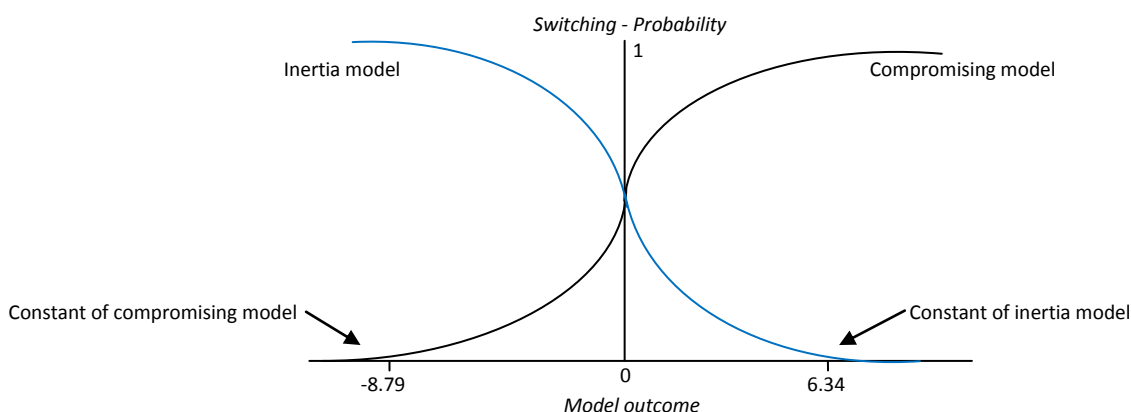
Figure 39: Schematic probability function for both sub-models.

The figure shows the schematic probability function for both sub-models (i.e. the model outcome in relation to the probability of the exposure of a certain choice behavior, in this figure summarized by switching and non-switching). If the values for the constants become closer to '0' there is a higher probability for switching behavior. The fact that the model performance decreases at these values for the constants, indicates that individuals are more likely to stick to their current choice or, in other words, are switch-aversive. This is a result of the fact that not much switching occurs within the used dataset, which might be because of, for instance, habitual behavior or that individuals believe they have chosen the best route alternative.

Furthermore, the models seem to be insensitive to values above 6.34 for the inertia sub-model and below -8.79 for the compromising sub-model (i.e. the model performance is constant for these values). This can be explained by the fact that the switching probability is already very low at the current values. One can imagine that even lower probabilities do not have any effect on the model performance anymore.

Remark that the principle of a lower model performance at higher switching probability as was illustrated using figure 39 applies to all attributes; using a 0% change in coefficient as the reference, an increase in a model coefficient results in a more positive model outcome, while a decrease in a model coefficient results in a more negative model outcome. Depending on the sub-model in which the attribute is included, the switching probability and thus the model performance will increase or decrease.

Figure 28 shows the model sensitivity to the attribute 'Time of day'. The model is only slightly sensitive to this attribute, as the model performance only changes within a range of about 4,5% point. Therefore, errors in this attribute will not influence the model results much. The same holds for the attribute 'Education' (see figure 29). On the other hand, the attributes 'Gender', 'Ethnicity' and 'Maximum Familiarity' seem to have nearly no influence on the model performance, as only a change in performance of about 1% point occurs (see figure 30, figure 31 and figure 32).

Figure 33 shows the model sensitivity to the attribute 'Driving years'. A decrease in performance is visible for lower values of driving years. A reason for this might be that individuals with less driving years make less consistent and systematic choices as they might not have that much experience in route choice making, which are therefore harder to predict correctly. Furthermore, less driving years is in general accompanied by lower ages. The lifestyle of younger people is often different from those who are older which might influence their route switching behavior. The model sensitivity to the attribute 'Residency', as shown in figure 34, shows a similar trend; a lower model performance for lower values of residency. At lower values of residency the familiarity with the road network is lower and less habitual behavior might exist influencing the route switching behavior of individuals.

It seems that the route choice model is sensitive to the included personality traits 'Extravertness' and 'Conscientiousness' (figure 35 and figure 36). A higher sensitivity is observed for the attribute 'Conscientiousness' which might be partly due to the fact that this attribute is included in both sub-models while the attribute 'Extravertness' only appears in the compromising sub-model. For both attributes, the model performance decreases at higher values. In other words, the model is not that accurate for more extreme personalities. Remember from chapter 4 that individuals with a high score on the personality traits consciousness or extravertness are assumed to make more switching

choices in order to attempt to pick the best route alternative or to get energized, relatively. Apparently, the model is not able to account for these high switching propensities.

One can imagine that the model would be highest sensitive to travel time differences between the route alternatives, as in the field of route choice modeling it is generally assumed that travel time is the main reason in making route choices. Therefore, the model sensitivity found in figure 37 and figure 38 for the difference in absolute travel time (included in the compromising sub-model) and the relative difference in travel time (included in the inertia sub-model) is not as expected. Changes in the influence of Δtt_{prev} do not seem to affect the model performance, while changes in the influence of Δtt_{abs} seem to only slightly affect the model performance.

Note that for some changes in the coefficients for several of the attributes the model performance exceeds the achieved model performance in case all original coefficient values are applied (i.e. 75.35%). This might occur because the regression model with the best model fit does not necessary result in the best model performance in terms of correctly predicted choices. Therefore, using these coefficient values that lead to higher model performance might overfit the model as it might describe random errors or noise in the data instead of the underlying relationship.

8.2   Discussion and conclusion

A drawback of the used approach changing one factor at a time, is that it does not fully explore the input space as it does not take into account the simultaneous variation of the input variables. Despite this, useful insights in the working of the model and its sensitivity to certain attribute values are obtained.

The route choice model seems to be insensitive to various values of the attributes 'Ethnicity', 'Maximum familiarity', 'Gender' and 'Δtt_{prev}'. This means that an error in those attribute values does not change the model results. This is a good thing as it makes the model robust on these issues. The model seems sensitive to the other attributes. Errors in these attribute values will obtain significant different outcomes. Therefore, these attributes should be investigated carefully before the model is applied to other situations and other contexts than those used in this research.

As the model is most sensitive to the model constants, this suggests that individuals generally have a strong preference for certain choice strategies, namely the non-switching strategies (i.e. minimizing in the compromising sub-model and inertia in the inertia sub-model), which is crucial in predicting their choice behavior correctly. In addition, it is found that the model is highly sensitive to the two personality traits that are included in the model, indicating that besides the model constants these individual-specific factors are apparently important in predicting choice behavior. Remarkably, they are of higher importance than the travel time attributes.

Overall, it can be reasoned that the developed model is not very robust as the model is sensitive to changes, and therewith to errors, in 9 out of 13 factors. Now, the next chapter will compare the developed 2-step-model with state-of-the-art models.

9 Model comparison

A route choice model is developed, improved and validated. The next research question is if this route choice model is an improvement and valuable addition to the state-of-the-art route choice models. Therefore, in this chapter the performance of the developed route choice model is compared to the performance of the most important and relevant state-of-the-art models. Section 9.1 determines which state-of-the-art models are interesting to include in the model comparison. Subsequently, section 9.2 elaborates on the principles and implementation of these state-of-the-art models. This is followed by the actual comparison in section 9.3. The chapter concludes with a discussion on the obtained model performances in section 9.4 and conclusions are drawn in section 9.5.

9.1 State-of-the-art models

The theoretical framework (chapter 2) covered the three most commonly used general choice models that are well applicable to route choice situations, as well as several choice models specifically designed for modeling route choices based on the behavioral mechanisms of route choice behavior. The most important and complete models are identified based on a literature review and considered for model comparison, namely:

- Utility Maximization Theory
- Prospect Theory
- Regret Theory
- Thresholds Theory
- SILK Theory
- Relaxing Assumptions Model
- Inductive Learning Model

Clearly, a comparison with the general and widely used choice models is valuable. This comparison indicates if the current modeling practice can be improved by using the newly developed model. Therefore, the newly developed model is compared to the utility maximization theory as this theory is based on the fundamental assumption of rationality that is highly criticized (see section 2.2.1), although it is still the most commonly used route choice modeling practice and can therefore be seen as the reference model. Subsequently, the prospect theory and regret theory will be applied, as these abandon the fundamental rationality assumption by taking an individual's loss and risk aversion and potential regret into account. In addition, Vreeswijk et al. (n.d.) and Chorus (2012b), among others, found evidence that drivers route choices are influenced by loss aversive and regret aversive behavior. This emphasizes the importance and relevance of a comparison of the newly developed model with these two models.

Besides comparison with general choice models, it is interesting to see how the newly developed route choice model performs in comparison with models that are specifically developed for modeling route choice behavior. As this research focuses on inertia and the accompanying inertia thresholds, the thresholds theory is highly relevant to this research. After all, this theory assumes that an individual i sticks to his route choice until some threshold value is exceeded. Furthermore, the SILK-Theory is interesting, because this theory combines most of the findings on route choice behavior found in literature into one model. Therewith, this might be the most complete route choice model in terms of capturing behavioral mechanisms. In addition, it makes use of if-then rules which are

based on certain threshold values for different variables. This makes this theory also relevant to this research.

The other two modeling theories, the Relaxing Assumptions Model and the Inductive Learning Model, are also interesting as the Relaxing Assumptions Model emphasizes on exactly those issues that the commonly used route choice modeling practice is criticized for and learning is found to be very important in route choice behavior. These models can therefore also be considered to be valuable in a comparison between different models. However, due to the limited amount of time available for this research, they are not considered to have enough relevancy to the main interest of this research to be implemented in the model comparison.

So, in this chapter the newly developed model will be compared to five existing modeling theories; Utility Maximization Theory, Prospect Theory, Regret Theory, Thresholds Theory and SILK-Theory.

9.2 Model implementation and results

This section elaborates on the principles and implementation of the state-of-the-art models that are found useful for comparison to the newly developed 2-step-model. In addition, the obtained results are shown for each model.

9.2.1 Newly developed 2-step-model

The newly developed model is implemented as described in chapter 5 using the parameter values that are obtained after re-calibration of the model (see chapter 6). The initial expected travel time for individual i was set to the average travel time on a certain route at the specific time of day for all observations in the dataset. These average travel times are closest to what the individuals might have experienced on an average day t and are therefore considered to be a good starting point. However, the model performance of the newly developed model is also tested using the general average travel time, which is based on all observations made on a certain route alternative for all individuals independent of the time of day. For subsequent choices a travel time smoothing method is used in order to determine the expected travel time for individual i at day t, which combines his expected travel time at day t-1 with his experienced travel time at day t-1 according to a certain weighting factor, i.e. smoothing factor α. A smoothing factor α of 0.01 was used, because in chapter 5 it was found that this method in combination with this smoothing factor value resulted in the best model performance.

For comparison it is also interesting to compare the 2-step-model with only the first step of the model (i.e. the dynamic expected shortest path module). After all, if this 1-step-model already performs very well or even performs better than the 2-step-model, there is no added value in applying the second step accounting for inertia when predicting route choice behavior. Different travel time updating approaches are tried for this 1-step-model as well. The first approach is the initially used averaging method, the second approach uses the smoothing method. Remember that the initially used averaging method determines the expected travel time of individual i at day t being the average of the experienced travel times by individual i until run t, while the smoothing method determines the expected travel time of individual i at day t combining his expected travel time at day t-1 with his experienced travel time at day t-1 (i.e. the smoothing method that is used in the 2-step-model). For comparison, first a smoothing factor α of 0.01 is used, as this was found to be the optimal value in the 2-step-model, using both the mean travel time in general and for the specific

time of day. For the 1-step-model based on the mean travel time in general, a smoothing factor α of 0.01 turned out to be optimal. However, the 1-step-model based on the mean travel time for a specific time of day, a smoothing factor α of 0.4 turned out to provide the highest performance. Therefore, only for the 1-step-model using the mean travel time for a specific time of day the model is also tested using a smoothing factor α of 0.4.

Results

Table 21 shows the model performances using different updating methods and initial travel times. It is found that a smoothing method using the general mean travel time obtains the highest performance for the 1-step-model, while a smoothing method based on the mean travel time for the specific time of day obtains the highest performance for the 2-step-model. The 2-step-model's performance turns out to be almost 4% point higher than that of the 1-step-model.

Table 21: Model performance of the 1- and 2-step-model using different updating methods and initial travel times

Correctly predicted route choices	1 step model - Dynamic Expected Shortest Path				2 step model - Dynamic Expected Shortest Path + Combined model	
	Averaging method	Smoothing method (α=0.01) (mean TT for Time of day)	Smoothing method (α=0.01) (mean TT general)	Smoothing method (α=0.4) (mean TT for Time of day)	Smoothing method (α=0.01) (mean TT general)	Smoothing method (α=0.01) (mean TT for Time of day)
Total correctly predicted [%]	65.13	61.19	71.67	66.05	67.70	75.35

Discussion

The parameter values of the combined model in the 2-step-model are estimated using an initial expected travel time based on the average travel time for a specific time of day. The same parameter values are used when the model is applied using the general mean travel time as initial travel time. If the model parameters were re-estimated a higher performance might be obtained. In fact, to address this issue correctly, re-estimating the parameter values would not be sufficient. New sub-models need to be developed, as the observed behaviors according to the definitions might change. After all, in some cases the shortest route during a specific time of day might not be the shortest route in general. This might even result in other variables to become important for explaining the observed choice behavior. However, because of time restrictions it is chosen to just apply the attributes and corresponding parameter values that are used in the 2-step-model as determined after re-calibration of the model during the model validation (see table 19 in chapter 6).

9.2.2 Utility Maximization/Shortest path Theory

The utility maximization theory is based on the fundamental assumption that all travelers are optimizers with perfect knowledge about their choice set. The utility V for a certain route i is given by the utility function, combining the influence of all different attributes together (Ortuzar & Willumsen, 2011):

$$V_i = \sum_j \beta_j * X_{ij}$$

where X_{ij} is the value of a certain attribute j on route i and β_j is the weight of this attribute. Remember from the theoretical framework that this is the simplest form of the utility theory.

In order to implement the utility maximization theory in the most simple and straightforward way possible, only the variable of travel time is considered. This variable is widely used and recognized as

most important variable in route choice behavior. It is assumed that the travel time is negatively related to utility; the higher the travel time on a certain route i, the lower the utility V_i. In fact, this simplification of the utility maximization theory reflects an individual minimizing his travel time. In other words, the individual chooses the shortest path.

This theory of individuals choosing the shortest path and therewith maximizing their utility is implemented as follows: the route alternative that is predicted to be chosen by a certain individual i is the route alternative with the lowest average travel time in general. It is likely that the time of day affects which route is the shortest route alternative. Therefore, the model is also applied using the average travel time for the specific time of day a certain individual i made his trip instead of the average travel time in general. Both travel times (i.e. average in general and average for a specific time of day) are calculated the same as earlier described in this chapter. This means that it is based on the average of all experienced travel times for the specific route within the dataset. The difference of the utility maximization method with the earlier described 1-step-model (i.e. dynamic shortest path method), is that the expected travel times on the route alternatives are not updated after each run t. In other words, the expected travel times are considered to be static. Therefore, each individual i will always choose the same route alternative for every run t in a certain choice situation c, that is, the route alternative that is on average the shortest.

Results

Table 22 shows the model performance of the utility maximization theory using different average travel times; the average travel time in general (i.e. average travel time per route alternative based on the whole dataset) and the average travel time for a specific time of day (i.e. average travel time per route alternative based on the observations that where obtained in respectively the morning, noon or evening peak hour). Note that the last approach using the average travel time for the specific time of day was also used in chapter 4 in comparison with the developed regression models.

Table 22: Model performance of Utility Maximization Theory using different average travel times

Correctly predicted route choices	Average TT general	Average TT for Time of day
Total performance [%]	75.78	61.19

It turns out that the utility maximization theory based on the average travel time in general outperforms the theory based on the average travel time specified to the different times of day. Apparently, individuals tend to choose the route alternatives that are generally the shortest alternative even if this is not the shortest alternative at that time of day.

9.2.3 Prospect Theory

The prospect theory is based on gains and losses that result from the different outcomes x of the choice options that are available to the choice maker with respect to a certain reference point. The value for the prospect of a certain route i is determined by the following formula (Kahneman & Tversky, 1979):

$$V_i = \sum_j \omega(p_j) * v(x_j)$$

where j represents the different outcomes x for route i, ω is the decision weight associated with the probability p of the jth outcome, reflecting the impact of p on the over-all value of the prospect, and $v(x_j)$ reflects the subjective value function of the deviations of outcome x_j from the reference point.

In route choice modeling this means that every route is associated with certain probabilities for different travel times to occur. Based on a certain reference point reflecting a certain travel time between OD-pair pq, there is a chance of experiencing a shorter travel time (i.e. gain) or higher travel time (i.e. loss) when using a certain route alternative of OD-pair pq. By defining the probability distribution of the travel times per route, the weights associated with these probabilities and the subjective value a certain individual i assigns to this travel time deviation with respect to his reference point, it is possible to calculate the value of the prospect of each route and compare these. In the end, it is assumed that the individual i will choose the route with the highest prospect value.

Avineri and Bovy (2008) suggest four approaches to set a value to the reference point when applying the prospect theory on route choices; based on mean or median travel time, using a direct way (i.e. deriving the parameter value from stated/revealed preferences) or using a mixed approach. A reference point based on mean or median travel time can be obtained using the observations from the available dataset and is a very straightforward method of defining a reference point. Due to perception errors the mean or median travel time might not be the actual reference point of an individual i. Therefore, setting a reference point using a direct way, which means that a certain individual i is directly asked for his reference point, might be more correctly. However, for this research this approach is laborious and time-consuming. Moreover, the individuals asked, might have other perceptions than the individuals that were involved during data collection of the used observations. The mixed approach incorporates elements of more than one approach and is dynamically updated because reference point values may differ from time to time and from one individual to another. Note that due to limited empirical research, it is still difficult to assess which of the suggested approaches would be best. Therefore, it can be concluded that within this research setting a value to the reference point based on the mean or median travel time obtained from the available observations is the most practical and straightforward. In this research, both the mean and median travel times are tested for the reference point.

Furthermore, certain outcomes x_j and the therewith associated probabilities p_j need to be determined. In order to do this, first, the empirical cumulative distribution function of the travel times per route alternative is determined using the data observations of the real-world experiment of all individuals and all times of day. Based on this distribution, the probabilities p_j for several outcomes x_j are calculated. These outcomes x_j are defined by creating seven bins based on the standard deviation σ and the mean travel time μ (i.e. the mean values of each bin are: -3σ, -2σ, -1σ, μ, 1σ, 2σ, 3σ, with a bin threshold of 0.5σ around these mean values), which is illustrated by figure 40.
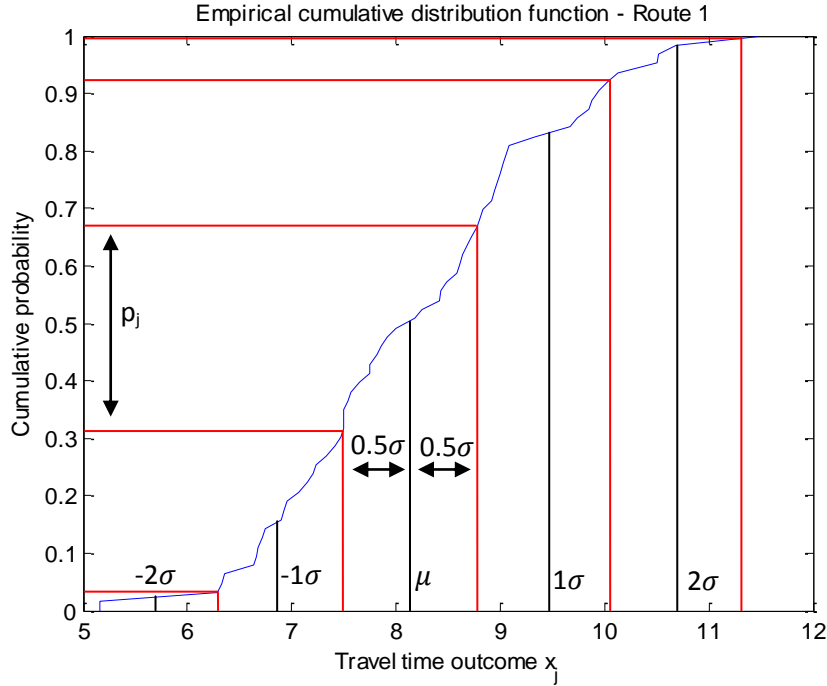
Figure 40: Illustration of determination of p_j and x_j for route alternative 1

Now the reference point, outcomes and probabilities are defined $v(x_j)$ and $\omega(p_j)$ can be calculated. Tversky and Kahneman (1992) provide the following functional form for defining $v(x_j)$.

$$v(x_j) = \begin{cases} x_j^{\alpha} & if\, x \geq 0 \\ -\lambda(-x_j)^{\beta} & if\, x < 0 \end{cases}$$

where the parameter λ describes the degree of loss aversion while parameters α and β ($\alpha \leq 1$, $\beta \leq 1$) measure the degree of diminishing sensitivity. The weighting functions $\omega(p_j)$ as proposed by Tversky and Kahneman (1992) are:

$$\omega^+(p_j) = \frac{p_j^{\gamma}}{\left(p_j^{\gamma} + (1-p_j)^{\gamma}\right)^{1/\gamma}}$$

$$\omega^-(p_j) = \frac{p_j^{\delta}}{\left(p_j^{\delta} + (1-p_j)^{\delta}\right)^{1/\delta}}$$

Where γ and δ measure the degree of curvature of the function.

As one can see, these formulas include some parameters that need to be estimated. In general, the estimation of the parameter values of the prospect theory is not much studied. Moreover, especially for predicting route choices, setting the parameter values is difficult; each individual i has different tastes, travel preferences, travel experiences and cognitive abilities. In order to set the different parameter values, first estimated values found in literature are tested. According to Chorus (2012b), this is common practice in applying the prospect theory.

It should be mentioned that in literature, no distinction per individual i is made and homogeneity among the population sample is assumed. In addition, the prospect theory is a static model and does therefore not account for changes over time. So, if a certain route alternative has the highest prospect value on OD-pair pq, the model will predict that all individuals i choose this route

alternative for all runs t (i.e. the prospect value does not change for each run t). In other words, the model only predicts the chosen route per OD-pair pq for all individuals. It is possible to detail the predictions for each individual i by estimating different parameters, reference points and distributions. However, determining these estimates is not easily done. In addition, assuming homogeneity is common practice for applying the prospect theory. Therefore, in this research the predictions are not detailed for each individual i.

Results

The different parameter values and resulting model performances are shown in table 23.

Table 23: Model performance of Prospect Theory under different parameter values found in literature

	Tversky and Kahneman (1992)	Tu (2005)	Andersen, Harrison, and Rutström (2006)	Harrison and Rutström (2009)	Booij, Van Praag, and Van de Kuilen (2009)
α (sensitivity)	0.88	0.68	0.81	0.71	0.859
β (sensitivity)	0.88	0.74	0.80	0.72	0.826
λ (loss aversion)	2.25	3.2	1.07	1.38	1.58
γ (curvature)	0.61	1.0	0.76	0.91	0.618
δ (curvature)	0.69	0.77	0.76	0.91	0.592
% total correctly predicted route choices *	**43.17**	**43.17**	**34.12**	**34.12**	**34.12**

*for each different set of parameter values a reference point of mean μ is used in order to apply the model

Remarkably, with different sets of parameter values, the same results are obtained. This indicates that the model is not very sensitive to the parameters. The sensitivity analysis in figure 41 underlines this finding, showing that for different values of a certain parameter (keeping the value of the other parameters constant) only two different results can be obtained. In addition, it is expected that the model would be more sensitive to the reference point as a change in this value certain gains might become losses and vice versa. However, changing the reference point from being the mean to median travel time of OD-pair pq did not change the performance of the model.
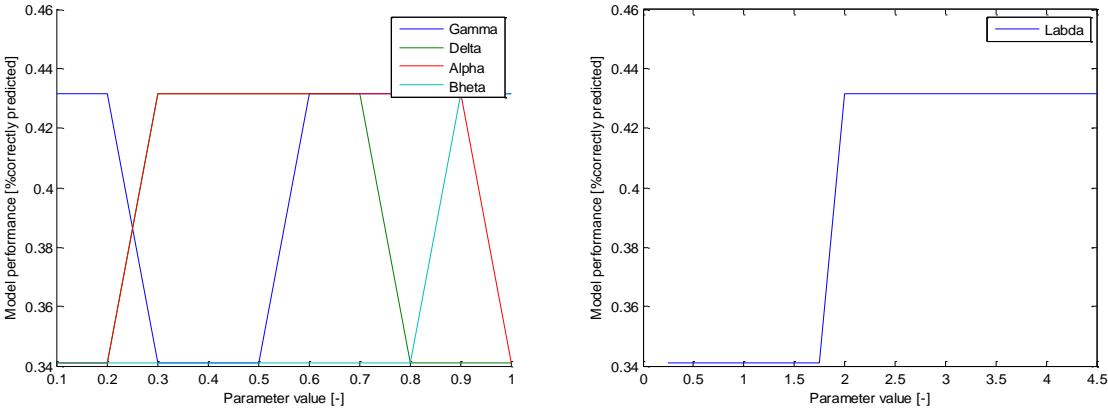
Figure 41: Sensitivity analysis for the different parameters of the prospect theory

Since the probabilities p_j for several outcomes x_j are calculated based on the empirical cumulative distribution function of the travel times per route alternative using all data observations of the real-world experiment, these probabilities and outcomes might be biased. Therefore, the leave-one-out method that was used for validating the newly developed model is applied. Remember that this approach leaves one of the observations out of the training set, influencing the distributions p_j, outcomes x_j and reference point of that choice situation c. Subsequently, the obtained model is

applied on the observation that was left out. This is repeated for every observation and resulted in an average correctly predicted route choices of 44.01% with a standard deviation of 49.66. The difference of the average outcome of the validation (i.e. 44.01%) and the initial model (i.e. 43.17%) is not that big. Therefore, it can be concluded that the initial prospect model is valid to use.

Discussion

The prospect model assumes that individuals have exact knowledge about the travel time distribution on each route alternative. One can imagine that this might not be very reality alike. Furthermore, all individuals are considered to be homogeneous in terms of their reference point, loss aversion and their subjective values and decision weights. It should be noted that this is common practice in using the prospect theory, although results might be improved if heterogeneous estimates would be used.

The observed lack of sensitivity for different parameter values is in this case expected to occur due to the fact that the model is not dynamic. Therefore, there are only five different choice situations within the used dataset on which the model is applied (i.e. the choice between the two route alternatives of the five OD-pairs). After all, the probabilities p_j and outcomes x_j do not change for both routes within the same choice situation c. The fact that the individuals are assumed to be homogeneous, fortifies that notion. This results in the same route choices being predicted by the model and these predictions will not easily alter by setting the parameter values slightly different.

In literature, there are found some more sophisticated models on prospect theory, which use different formulas for the weighting functions and subjective value functions sometimes introducing additional parameters. Several of these theories are elaborated upon by Booij et al. (2009). It is possible that one or more of these sophisticated models obtain better results.

9.2.4 Regret Theory

The regret theory is based on the basic idea that after making a choice, individuals will reflect on how much better or worse the consequence of their chosen option could be if they had chosen differently. This postulates that people will make a choice in such a way that none of the other options will outperform the chosen alternative and therewith choose the option they are likely to regret the least. This theory can be applied using the expected modified utility function (Chorus, 2012b):

$$EMU_A = \sum_s \left[p_s * \left(\frac{1 - \exp(\theta * t_s^A)}{\theta} + \left[1 - \exp\left(-\delta * \left[\frac{\exp(\theta * t_s^B) - \exp(\theta * t_s^A)}{\theta} \right] \right) \right] \right) \right]$$

$$EMU_B = \sum_s \left[p_s * \left(\frac{1 - \exp(\theta * t_s^B)}{\theta} + \left[1 - \exp\left(-\delta * \left[\frac{\exp(\theta * t_s^A) - \exp(\theta * t_s^B)}{\theta} \right] \right) \right] \right) \right]$$

where A and B represent the different routes. s represents the different 'states of the world', each state being characterized by a probability of occurrence p_s, and different combinations of travel times for the two routes (t_s^A, t_s^B). θ is the risk aversion parameter and δ represents regret aversion. Higher values of θ correspond with higher levels of risk and when δ increases, regret becomes more important in making the choice. The route alternative with the highest expected modified utility (i.e. EMU) will be chosen by the individual i.

The same calculations of the probabilities p_j and travel times x_j from the Prospect Theory (see figure 40) are used in this regret approach. The travel times t_s^A and t_s^B correspond to x_j^A and x_j^B. The probability of occurrence of the 'state of the world' p_s, in which t_s^A and t_s^B both occur, is calculated multiplying the probability of occurrence of t_s^A, which is p_j^A, by the probability of occurrence of t_s^B, which is p_j^B. This means that 49 (i.e. 7 times 7) different 'states of the world' s are considered.

It should be mentioned that, just like in applying the prospect theory, no distinction per individual i is made and homogeneity among the population sample is assumed. In addition, the regret theory is also a static model and does therefore not account for changes over time. So, if a certain route alternative has the highest expected modified utility EMU on OD-pair pq, all individuals i are expected to choose this route alternative for all runs t. In other words, the model only predicts the chosen route per OD-pair pq for all individuals. It is possible to detail the predictions for each individual i by estimating different parameters and distributions. However, determining this estimates is not easily done. Therefore, in this research the predictions are not detailed for each individual i.

Results

Different combinations of parameter values for δ and θ are tried with a magnitude in accordance with the parameter values tested by Chorus (2012b) in order to find the best model performance. Table 24 shows the model performances under different combinations of these parameter values. When no risk aversion (i.e. θ=0) and regret aversion (i.e. δ=0) is presumed, the model performance is low. However, for other values of θ and δ the model performance increases. Remark that, just like for the prospect theory, different parameter values lead to only a few different outcomes in model performance.

Table 24: Model performance of Regret Theory under different combinations of parameter values for δ and θ

Parameter values – Performance [%]		θ (risk aversion)										
		0	0.005	0.01	0.015	0.02	0.025	0.03	0.035	0.04	0.045	0.05
δ (regret aversion)	0	44.76	56.83	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.025	44.76	56.83	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.05	44.76	56.83	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.075	44.76	56.83	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.1	44.76	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.125	44.76	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.15	44.76	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.175	44.76	56.83	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.2	44.76	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.225	44.76	56.83	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88
	0.25	44.76	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88	65.88

Since, again, the probabilities p_s for several travel times t_s^A and t_s^B are calculated based on the empirical cumulative distribution function of the travel times per route alternative using all data observations of the real-world experiment, these probabilities and travel times might be biased. Therefore, the leave-one-out method that was used for validating the newly developed model is applied. Remember that this approach leaves one of the observations out of the training set, influencing the distributions p_s and outcomes t_s of that choice situation c. Subsequently, the obtained model is applied on the observation that was left out. This is repeated for every observation and resulted in an average correctly predicted route choices of 65.21% with a standard deviation of 47.65. The difference of the average outcome of this validation (i.e. 65.21%) and the initial model

(i.e. 65.88%) is not that big. Therefore, it can be concluded that the initial prospect model is valid to use.

Discussion

The regret theory suffers from the same limitations as the prospect theory; not reality alike knowledge of travel time distributions on each route alternative, a homogeneous population and not being dynamic. Again, this results in the lack of sensitivity to the parameter values that is being observed.

In literature, there are found some more sophisticated models on regret theory, such as the random regret minimization theory. This theory postulates that 'as long as alternatives are characterized in terms of multiple attributes, there will be regret in the sense that there will generally be at least one non-chosen alternative that outperforms a chosen one in terms of one or more attributes (Chorus, 2012a). These more sophisticated models might increase the performance of the regret theory.

9.2.5 Thresholds Theory

The threshold theory by Carrion and Levinson (2012) is based on the idea that a traveler determines a certain travel time threshold and therewith creates an acceptable time margin for trips on a specific route alternative. The experienced travel times by a certain traveler on that route alternative are assessed related to this acceptable time margin. Depending on the frequency of experienced travel times within and outside this acceptable time margin, individuals may decide to abandon the currently chosen route alternative and switch to another route. The theory was originally intended for predicting absolute long-term switches and not the day-to-day dynamics that is focused on in this research. However, one can imagine that the basic idea might as well apply to day-to-day dynamics.

There are two different models suggested; the Fixed Threshold model, which assumes that individuals have a strict expectation about their travel times and travel time variability, and the Moving Threshold model, which assumes that individuals continuously update their margins based on the experienced travel times of the previous trips. Both models assume a moving set of travel times that represents the past trips that individual i remembers. Carrion and Levinson (2012) use 2 to 15 days before the specific day of travel of a trip. However, the dataset used in this research only contains 20 trips for each OD-pair pq made by individual i. Therefore, all the experienced travel times on a certain OD-pair pq by a certain individual i are used in this research. In other words, it is assumed that individuals can recall all their experienced trips during the real-world experiment.

This limited amount of trips per OD-pair pq for each individual i enforces some limitations on how to implement the theory without endangering the comparison with the other models. For the moving thresholds model it is hard to decide on a method to determine the mean and standard deviations for the first few runs in a dynamic way. In addition, the primary results found by Carrion and Levinson (2012) indicate that the fixed thresholds model should be preferred for capturing route switching dynamics. Therefore, it is decided to only apply the fixed threshold model.

The fixed thresholds are determined calculating the mean μ and associated standard deviations σ of each route alternative based on all observations of all individuals in the dataset. Remember from the literature review in section 2.3.7 that trips above the threshold are referred to as late trips and trips below the threshold as early trips. Trips within the thresholds are referred to as regular trips.

Individuals are more likely to leave their current route if the number of late trips increases and more likely to stick with their current route if the number of early trips increases.

Different criteria can be proposed in order to predict if a certain individual i will switch his route choice or stick to his current choice. The first criterion, that follows directly from the abovementioned, states that if individual i experienced more late trips than early trips on a certain route m, he will switch his route (i.e. $\#trips_{early,m} < \#trips_{late,m}$). As one can imagine, regular trips might also contribute to the likeliness that a certain individual i will stick to his current route choice. After all, regular trips indicate that the route alternative performs as expected and this expectation was most likely the reason why this route alternative was chosen in the first place. Therefore, the second criterion states that an individual i will change his route choice if there are more late trips experienced by this individual i than regular trips and early trips together on route m (i.e. $\#trips_{early,m} + \#trips_{regular,m} < \#trips_{late,m}$). The last criterion is only based on the late trip ratio which might exceed a certain value as late trips in this context can be considered to be the main reason for route switching (i.e. $\#trips_{late,m}/\#trips_{total,m} > x$, where $x \leq 1$). If this value of x is set to 1, it is assumed that individuals always sticks to their current choice.

In addition to setting the switching criterion, the margins for classifying early and late trips need to be set. Carrion and Levinson (2012) found that a standard deviation σ of 0.5 below mean μ was significant for classifying early trips, while in classifying late trips a standard deviation σ of 1 above mean μ turned out to be significant (at a 5% significance level). Therefore, different combinations of these values are tested.

Note that, opposed to the utility maximization theory, prospect theory and regret theory, with this threshold theory the predicted choice for a certain route m can differ per individual i and over time t.

Results

Table 25 shows the model performance of the threshold theory under those different combinations of σ under different switching criteria. Note that the last criterion (i.e. $\#trips_{late,m}/\#trips_{total,m} > 1.0$) implies that one always sticks to the chosen route m at t-1, even if all trips are classified as being late trips. This criterion obtains the best model performance on all threshold values. So, there is no highest model performance achieved on only one of the threshold combinations. However, threshold values of *μ-0.5σ* and *μ+1.0σ* obtain the best model performance on all 4 criteria. Therefore, these threshold values are considered to be most suitable.

Table 25: Model performance of Threshold Theory under different combinations of σ and different switching criteria

Switch criterion: \ Threshold	μ-0.5σ, μ+0.5σ	μ-1.0σ, μ+1.0σ	μ-0.5σ, μ+1.0σ	μ-1.0σ, μ+0.5σ
$\#trips_{early,m} < \#trips_{late,m}$	43.47%	38.76%	48.09%	35.64%
$\#trips_{early,m} + \#trips_{regular,m} < \#trips_{late,m}$	59.73%	74.04%	74.04%	59.73%
$\#trips_{late,m}/\#trips_{total,m} > x*$	77.60% (x=0.9)	78.76% (x=0.7-0.9)	78.76% (x=0.7-0.9)	77.60% (x=0.9)
$\#trips_{late,m}/\#trips_{total,m} > 1.0$	79.02%	79.02%	79.02%	79.02%

* Only the x (x=0.1 till x=0.9, step size is 0.1) which obtains the highest model performance, is shown.

Discussion

Although the model was intended for long-term switching it seems to capture day-to-day dynamics quite well. Because of the limited number of runs in the dataset for each OD-pair pq the first few runs are based on less experienced travel times than a certain individual i would recall (i.e. the switching criteria are calculated based on less than 15 trips). For individuals that were unfamiliar with the available route alternatives this would be reality alike. However, most of the individuals in the dataset were already familiar with the options. This might indicate that the model could perform even better if more runs were available.

9.2.6 SILK-Theory

The SILK theory concerns about how travel decisions are actually made and emphasizes on the role of Search, Information, Learning and Knowledge in travel decision-making. The theory consists of a conceptual framework (figure 42) that includes the interaction between the individual level and the road network level. It updates the knowledge, belief and expectations of individual i based on the network conditions. Subsequently, based on the search gain and search cost it is determined which two route alternatives are considered. As in this research, only two route alternatives are available in each choice situation c, this route search part of the theory is left out at the implementation of the theory on the available dataset. As a result, updating the expectation by computing the subjective search gain and comparing this to the search cost is not necessary anymore.
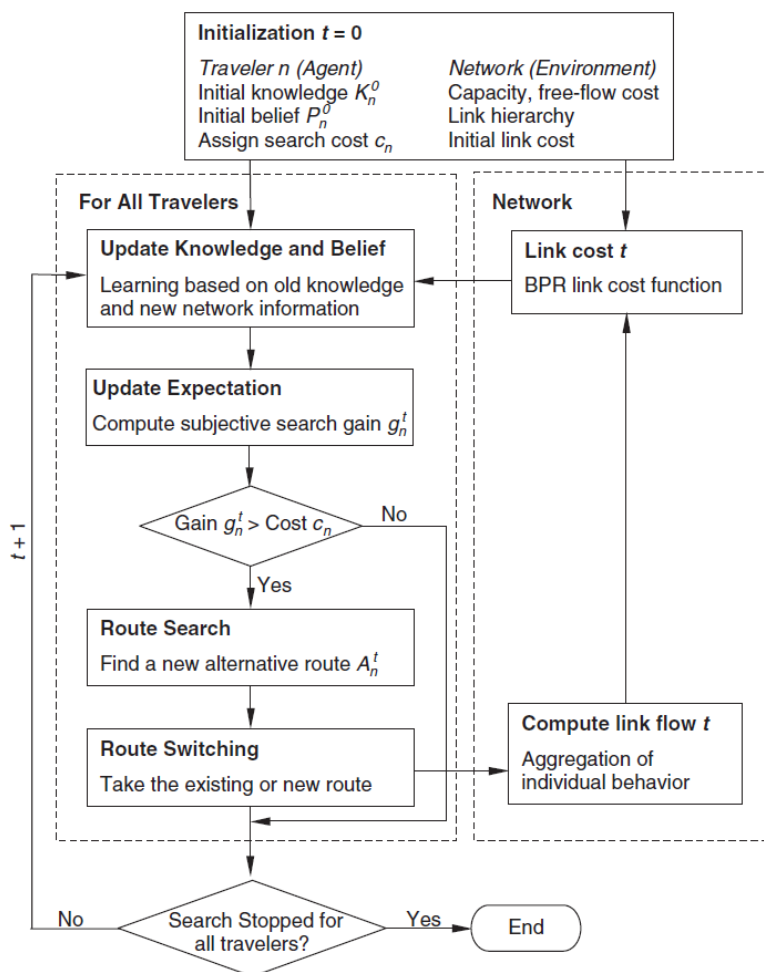

Figure 42: Conceptual framework of the travel decision-making process in SILK (Zhang, 2011).

For updating the knowledge and beliefs the expected travel time for both route alternatives is determined based on the smoothing method using a smoothing factor α of 0.01 (i.e. the smoothing factor α that is used in the newly developed model) at each run t. Based on this expected travel time and the free flow travel time on each route alternative the expected delay for each run t is calculated. In order to replicate the heuristics individuals use to (not) switch routes, Zhang (2006a) used the following if-then rules:

Change route, if

[ΔTime ≤ -39%]	**Rule 1**
or [ΔTime ≤ -11% and ΔPleasure ≥ -1]	Rule 2
or [ΔFamiliarity ≥ 3 and Commute time ≤ 20 min]	**Rule 3**
or [ΔTime ≤ 6% and ΔPleasure ≥ 3]	Rule 4
or [ΔTime ≤ 15% and ΔFamiliarity ≥ 2 and ΔDelay ≥ -40%]	**Rule 5**
or [Familiarity = 1 and ΔTime ≤ 51% and Commute time ≤ 20 min and Income = 1]	Rule 6
or [Delay ≥ 4 min and ΔStops ≤ 0 and Commute distance ≤ 8 miles]	**Rule 7**
or [ΔPleasure ≥ 2 and ΔFamiliarity ≥ 0 and Commute time ≤ 16 min]	Rule 8
Otherwise, continue to use the current route.	**Rule 9**

These rules cannot be directly applied to the available dataset as several variables (i.e. Δpleasure and income) are not accounted for in this dataset. Therefore, the rules containing these variables (i.e. rule 2,4,6 and 8) are simply excluded from implementation. Furthermore, Zhang (2006a) used a 7-point scale in order to measure familiarity, while the available dataset in this research uses a 5-point scale. Therefore, these numbers are normalized.

First, all parameter settings proposed by Zhang (2006a) are used to apply the SILK-theory on the available dataset. Then, different values are adapted to be more in line with the current available dataset, using a trial and error approach. The next paragraph will elaborate on this.

Results
When the if-then rules are now implemented, using the same threshold values as provided by Zhang (2006a), the model predicts 62.48% of the observed route choices correctly. However, within the available dataset there are no observations with an expected time difference bigger than -39%[4], almost all commute times are lower than 20 minutes and only one out of the ten routes has a commute distance of over 8 miles. Therefore, adapting these threshold values to be more in line with the current available dataset might improve the model performance. In order to do so, a trial and error approach is used. It is found that an increase in the threshold value of the expected travel time difference of rule 1 lowers the model performance, which is not desired. Lowering the threshold value of the commute time in rule 3 from 20 minutes to 6.4 minutes increases the model performance to 64.36%. Lastly, lowering the threshold value of the commute distance in rule 7 from 8 miles to 5 miles did increase the model performance even more, namely to 66.22%. However, it should be noted that there is now only one out of the ten routes shorter than 3 miles, instead of the initial case in which only one out of the ten routes was longer than the threshold value. When the other threshold values are tested, it was found that increasing the value for difference in delay in rule 5 from -40% to -34% would improve the model performance even more, namely to 71.38%,

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[4] The minus indicates that the route that was not chosen should be the shorter one. In other words, there should be an expected decrease in travel time of 39% if an individual switched to the other route alternative.

while the other threshold values resulted in a worse model performance or had no influence on the model performance at all. These findings are summarized in table 26.

Table 26: Model performance of the SILK-Theory under different threshold values found by trial and error.

Threshold Values	Values of Zhang	Rule 3: Commute time≤6.4 min, + values of Zhang	Rule 7: Commute distance ≤ 5 miles, Rule 3: Commute time≤6.4 min, + values of Zhang	Rule 5: ΔDelay ≥ -34%, Rule 7: Commute distance ≤ 5 miles, Rule 3: Commute time≤6.4 min, + values of Zhang
Correctly predicted route choices [%]	62.48	64.36	66.22	71.38

Discussion

Although not all if-then rules that were formulated by Zhang (2006a) could be implemented in this research the model already performs reasonably well after adjusting some of the threshold values to be more in line with the available choice situations. One can imagine that the results might be even better when the excluded rules could also be implemented.

9.3 Comparison and findings

In order to compare the models that are introduced in the previous sections and implemented on the dataset used in this research, the specifications of each model that results in the best model performance for that specific theory are identified. The model performance results are listed in table 27. Besides the total performances, the table shows also the more detailed results for the different OD-pairs pq, runs t and driver types d.

Table 27: Overview of the model performance of 7 route choice models applied on the case of this research.

Correctly predicted route choices	2-step-model - Dynamic Expected Shortest Path + Combined model	1-step-model - Dynamic Expected Shortest Path	Utility Maximization / Shortest path theory	Prospect Theory	Regret Theory	Threshold Theory (fixed)	SILK-Theory
	Smoothing method (α=0.01) (mean TT for Time of day)	Smoothing method (α=0.01) (mean TT general)	Mean TT general	Parameter values of Tversky and Kahneman (1992)	Parameter values: θ=0.025, δ=0.125	Threshold: Mean-0.5σ, Mean+1.0σ Criterion: Late trip ratio >1.0	ΔDelay ≥ -34%, Commute distance≤5 miles, Commute time≤6.4 min, + rest of values of Zhang (2006a)
OD-1 [%]	67.26	54.10	74.18	74.18	25.82	73.91	74.78
OD-2 [%]	76.37	65.96	65.96	34.04	65.96	80.83	47.37
OD-3 [%]	78.67	76.09	76.09	23.91	76.09	83.21	84.64
OD-4 [%]	71.75	80.34	80.34	80.34	80.34	73.81	73.81
OD-5 [%]	82.33	87.50	87.50	12.50	87.50	81.22	79.56
First 10 runs *t* [%]	63.40	60.04	63.13	36.49	57.92	65.11	59.11
Last 10 runs *t* [%]	84.52	80.59	85.48	48.30	72.00	88.30	79.56
Driver type 1 [%]	-	-	-	-	-	-	-
Driver type 2 [%]	89.98	79.65	88.26	31.31	79.26	97.72	83.82
Driver type 3 [%]	66.92	67.50	69.66	52.42	56.55	68.57	64.95
Driver type 4 [%]	53.13	57.60	52.00	50.40	52.80	49.15	49.15
Total correctly predicted [%]	75.35	71.67	75.78	43.17	65.88	79.02	71.38

Figure 43 shows the results of table 27 in a more visual manner.
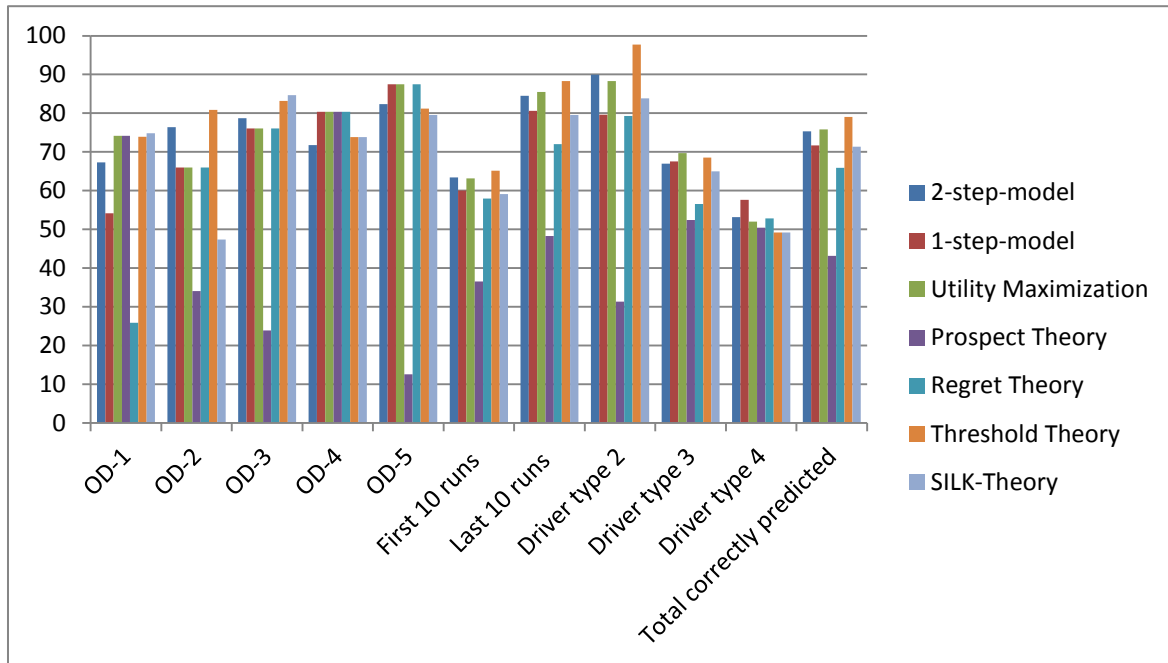
Figure 43: Visual overview of the model performance of 7 route choice models applied on the case of this research.

The threshold theory performs the best of all 7 models, closely followed by the utility maximization theory and the newly developed 2-step-model. In addition, the 1-step-model (i.e. the first step of the 2-step-model) and the SILK-theory perform also quite well. As one of the recently proposed new route choice models based on the behavioral mechanisms of the indifference band, the high performance of the fixed threshold model is quite a nice finding. Both theories based on risk aversion, loss aversion and regret perform the worst of all models in the comparison. This might be the case because of their static nature and their insensitiveness to their parameter values when applied to the cases of this research.

The fact that the shortest path theory outperforms the 1-step-model indicates that an updating process for the expected travel time is probably not necessary as it seems to deteriorate the average model performance from 75.78% to 71.76%. The addition of the second step of the 2-step-model accounting for inertial behavior then raises the model performance back up to 75.35%. So, replacing the first step of the 2-step-model by the shortest path theory (i.e. leaving out the expected travel time updating process) might result in higher model performance. In this research this was not done, as the objective was to develop a dynamic model, while this approach will transform the 2-step-model into a static model.

All 7 models turn out to be better in predicting route choices in the last 10 runs t than in the first 10 runs t of a certain choice situation c. As mentioned earlier in chapter 4, this finding is as expected. It seems that the threshold theory performs the best of all assessed models on the last 10 runs t, indicating that for daily route choice predictions over a long period the threshold theory might be the best model to apply. The expectation that this model would perform even better if a longer time-span, containing more runs t, is used, as suggested when this theory was introduced (section 9.2.5), emphasizes this indication.

Six of the models achieve the best prediction results of all driver types d on driver type 2. One exception is the prospect theory, which obtains lower model performance on this driver type than on the other two (i.e. driver type 3 and driver type 4). In addition, driver type 4 is in general the worst predicted. One can imagine that it is harder to predict choice patterns of individuals with a high switching tendency than that of individuals who choose the same route alternative over and over again, which explains this finding. In addition, note that the higher the driver type number, and therewith the number of switches within the driver type, the more similar the model performances of the different models are. The threshold theory achieves a model performance of an impressive 97.72% on driver type 2. The 2-step-model also achieves a high model performance on this driver type (89.98%), which places the model on the second place compared to all other models. In addition, the 2-step-model performs relatively well on driver type 4. These notions indicate that the 2-step-model would be relatively valuable to use especially for these driver types d. In fact, several models can be identified that might be the most valuable to use in predicting daily route choices of certain driver types. Table 28 provides an overview.

Table 28: Overview of the different driver types d and their best performing models

Driver type d	Characteristics	Best model to use
1	- No switching at all - Satisfied with route choice	Not applicable
2	- Almost no switching (i.e. low switching level) - High preference for one route alternative	2-step-model + Threshold theory
3	- Some switching (i.e. medium switching level) - Slight to medium preference for one route alternative	Shortest path theory + Threshold theory
4	- Much switching (i.e. high switching level) - No preference for one route alternative	2-step-model + 1-step-model

In predicting route choices on the different OD-pairs pq there is some more variation among the different model performances; some models perform very well on a certain OD-pair pq, while others perform badly on the same OD-pair pq. On another OD-pair pq this might be the opposite; the model that performed badly on the first OD-pair pq performs very well on the next OD-pair pq, while the model that performed very well on the first OD-pair pq, performs badly on the next OD-pair pq. For example, the regret theory performs badly on OD-pair 1 (25.82%), while it performs very well on OD-pair 5 (87.50%). On the opposite, the prospect theory is performing very well on OD-pair 1 (74.18%), while the performance on OD-pair 5 is dramatically low (12.50%). This notion suggests that in different choice situations different models would be valuable to use.

OD-pair 1 has the smallest difference in travel time between the two route alternatives and it has the biggest difference in number of merges and diverges of all 5 OD-pairs. Furthermore, almost half of the choices made on this OD-pair are defined as being an inertial choice (based on expected travel times using the smoothing approach (α=0.1) with initial expected travel times specified per time of day). In this choice situation the route choices are best predicted by the SILK-theory, closely followed by the shortest path theory and the prospect theory.

OD-pair 2 contains the trip with the highest travel time of all OD-pairs. In addition, both route alternatives have a high number of horizontal curves compared to the other OD-pairs. In this choice situation the 2-step-model and the threshold theory outperform the other five models significantly.

OD-pair 3 has one route with significantly higher traffic volumes. Other than this, it is an average trip with no extreme characteristics. On this OD-pair, the SILK-theory and the threshold theory perform the best and would therefore be most valuable to use.

OD-pair 4 contains route alternatives with the highest difference in average travel speed, although the average difference in travel time is low. Furthermore, there is no difference in number of stops between the route alternatives, while one of the route alternatives passes through a busy university campus area. Just like for OD-pair 1, almost half of the choices made on this OD-pair are defined as being an inertial choice (based on expected travel times using the smoothing approach (α=0.1) with initial expected travel times specified per time of day). In this choice situation the theories on dynamic expected shortest path, shortest path, prospect and regret perform the best. Note that the shortest path theory and the prospect theory were also the best models to use for OD-pair 1, which is on some of the trip characteristics comparable to OD-pair 4.

OD-pair 5 has the largest difference in travel time and number of stops between the two route alternatives compared to the other OD-pairs. In addition, it has the lowest difference in travel speed and the lowest percentage of inertial choices (based on expected travel times using the smoothing approach (α=0.01) with initial expected travel times specified per time of day). In this choice situation the theories on dynamic expected shortest path, shortest path and regret predict the observed route choices the best.

Table 29 summarizes these findings. Note that the overall least performing models still turn out to be valuable in predicting route choices in certain choice situations. Moreover, the overall best performing threshold theory is most valuable in only two choice situations. The newly developed 2-step-model seems to be valuable to use in choice situation 2. Remarkably, the 2-step-model is not among the most valuable theories to use in choice situations in which a high percentage of the choices are defined as an inertial choice.

Table 29: Overview of the different choice situations and their best performing models

OD-pair pq	Characteristics	Best models to use
1	- lowest $\Delta TT_{average}$ - highest Δmerges+diverges - highest % of choices are defined as inertia (~50%)	SILK-theory, Shortest path theory, Prospect theory
2	- highest travel time - high number of horizontal curves	2-step-model + Threshold theory
3	- one route with higher traffic volume	SILK-theory + Threshold theory
4	- highest Δtravel speed - low $\Delta TT_{average}$ - no difference in #stops/intersections - one route passes through busy campus area - highest % of choices are defined as inertia (~50%)	Dynamic expected shortest path theory, Shortest path theory, Prospect theory, Regret theory
5	- highest $\Delta TT_{average}$ - highest difference in #stops/intersections - lowest Δtravel speed - lowest % of choices are defined as inertia	Dynamic expected shortest path theory, Shortest path theory, Regret theory

Furthermore, it can be seen that the threshold theory has the highest minimum performance for the different OD-pairs (73.81% on OD-pair 4) of all models, although it is closely followed by the 2-step-model and shortest path theory. This indicates that the threshold theory is most constant in predicting route choices in different situations.

In order to continue, note that the 1-step-model, shortest path theory, prospect theory and regret theory achieve the same performances on some of the OD-pairs. This is not that remarkable. First of all, the principle of the 1-step-model and the shortest path theory are quite the same; they both assume an individual i chooses the route alternative with the shortest travel time. Only, the (expected) travel times on which the principle is applied differs from each other, as the shortest path

theory uses a static general average, while the 1-step-model uses a dynamic updating process resulting in expected travel times. Due to the very small smoothing factor α that is used in the 1-step-model, the (expected) travel times which are used in the different models are almost the same. As a result, the performance of the two models differs only on OD-pair 1, which has the smallest travel time difference in general (a difference of 0.1 minute).

Secondly, this indicates that in certain choice situations it does not make a difference which assumption is used; assuming individuals rationally choose the shortest route or assuming individuals route choices are influenced by risk aversion, loss aversion and regret. Apparently on these 5 OD-pairs the route alternatives causing the least regret (or, to a lesser extent, the least losses and risks) are also the shortest route alternatives. One should note that this is not necessarily the case for every OD-pair in general as is emphasized by the results on, for example, OD-pair 1.

Now, figure 44 shows the model performances detailed for each of the 1193 observations within the dataset. First, the model performance of the 2-step-model is shown for reference. Figure 44a till f compare the performances of the 2-step-model with each of the state-of-the-art models. It can be seen that the 1-step-model and shortest path model slightly follow the performance trend of the 2-step-model; if the 2-step-model has a high model performance on certain observations, these are also correctly predicted by the 1-step-model and shortest path model, while the observations containing a drop in model performance by the 2-step-model seem to be also incorrectly predicted by the other two models. This is not the case for the prospect theory and the regret theory. Their model performances for some of the observations tend to be low while the model performance of the 2-step-model is high on these specific observations. The trend of the model performance of the threshold theory and SILK-theory look quite different from the other model performance trends; while most model performance trends contain clusters of correctly predicted observations and incorrectly predicted observations, the performance trends of the threshold theory and SILK-theory are more alternating. In general, the observations that seem to be the hardest to predict by all the models can be found in the clusters around observation 400, 600, 800 and 1100.
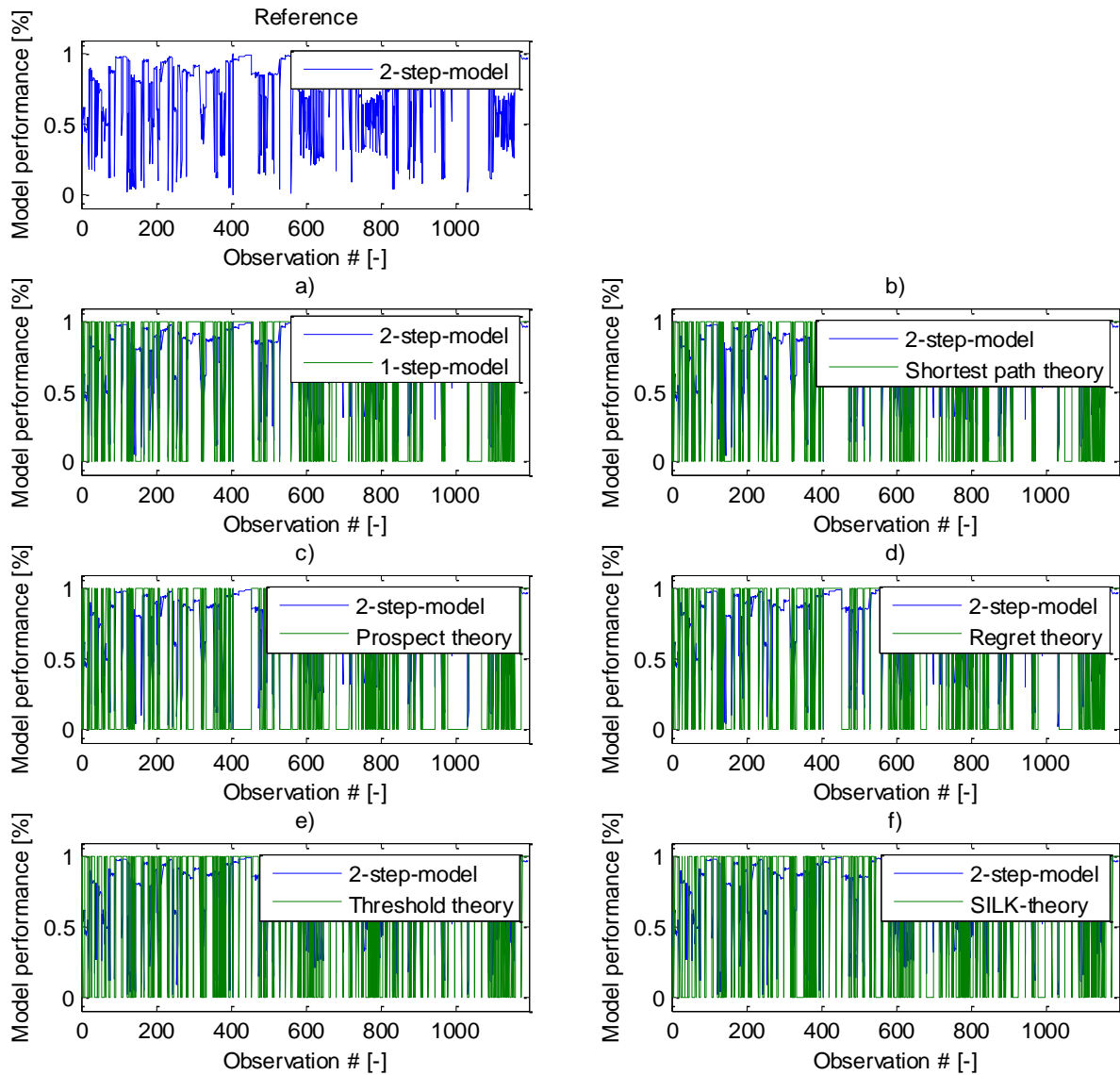
Figure 44: Model performance of the 6 state-of-the-art models compared to the 2-step-model for each observation

9.4 Discussion on model performances

The finding that in circa 76% of all observations the shortest path is chosen, is quite high compared to results found in literature. Zhu and Levinson (2012) found that only 34% of the trips made by 143 commuters in Minnesota, USA, followed the shortest time path. Bekhor, Ben-Akiva, and Ramming (2006) found a comparable 37% for trips reported by 188 staff members from the Massachusetts Institute of Technology in the Boston area, USA. In addition, a revealed preference study among faculty and staff members of Turin Polytechnic in Turin, Italy, showed that in 43% of the trips the shortest route alternative was used. However, Thomas and Tutert (2010) obtained a similar result as found in this research; for about 75% of the trips the shortest time route was observed during a license plate study in Enschede, The Netherlands. The high percentage of individuals choosing the shortest path in the used dataset in this research might be a result of the fact that only 5 OD-pairs are used in the experiment containing a small number of only 20 participants. More variation in participants and OD-pairs might lead to less travel time minimizing choices. In addition, the definition of shortest path might alter the model performances significantly, as can be seen from table 22. It is not clear which definition the other researches used. A last explanation can be given by the fact that

in this research only two route alternatives were available to the individuals to choose from, while in the aforementioned researches almost unlimited route alternatives were available. One can imagine that it would be easier to identify the shortest route alternative out of two route alternatives than out of many route alternatives.

De Moraes Ramos, Daamen, and Hoogendoorn (2011) applied the prospect theory on their case modeling travelers' route choice behavior as prospect maximizers and found a model performance between 47.7% and 51.1%. In this research a slightly lower model performance for the prospect theory is obtained; only 43.17%. In addition, De Moraes Ramos et al. (2011) found a model performance for the regret theory between 48.8% and 52.0%, which is significantly lower than the 65.88% that is obtained in this research. For the fixed threshold theory and SILK-theory no results were found in literature.

To put the obtained model performances in context; predicting route choices by choosing them randomly (i.e. each route alternative has an equal probability to be chosen, in this case 50%) results in about 50% of the route choices being correctly predicted on average. Therefore, it can be stated that in general the prospect theory has no added value to route choice modeling with respect to random predictions, while the other models do have some added value.

The findings show that the model performances are highly dependent on the cases (i.e. OD-pairs) they are applied to. This was also indicated by the results found in the model performance comparison. Some models might perform better in choice situations containing for instance relatively long trips or city routes, while others might be of better use at for instance certain trip purposes. However, with the 5 OD-pairs used in this research it is not that easy to identify which model would be best to use in which circumstances.

In general, it seems that for these 5 OD-pairs the model results of each model are reasonable compared to findings in literature. As the performances of the SILK-theory and fixed threshold theory, for which no results could be found in literature, are comparable to the results of the other state-of-the-art models, these can also be considered reasonable.

9.5   Conclusion

The newly developed 2-step-model is compared to 6 other models; the 1-step-model (i.e. first part of the 2-step-model), the Utility Maximization Theory (i.e. shortest path theory), the Prospect Theory, the Regret Theory, the Threshold Theory and the SILK-Theory. Although for the implementation of some of these theories the available dataset brought some limitations, reasonable solutions are found for implementation and results comparable to literature findings are obtained.

It is found that the model performance of the developed 2-step-model is comparable to those models with the highest performances. However, the simple, general applicable and in current route choice modeling practice vastly applied shortest path theory and the quite recently introduced threshold theory developed for long term route choice predictions turned out to be on average the best performing models in this research. In addition, the developed 2-step-model is the second-best in terms of consistency of the models, which means it is less sensitive for differences in characteristics of the choice situation. Economic choice models based on risk aversion, loss aversion and regret (i.e. prospect theory and regret theory) are found to be less suitable in predicting the

observed route choices. The recently introduced behavioral route choice model based on the notion of the indifference band and boundaries in route switching (i.e. the SILK-theory) is performing reasonably well.

The performances for each model are detailed for each OD-pair pq, the first and last 10 runs t and driver type d. The results on this detailed level indicate that certain models perform better in certain choice situations than others. It is tried to specify which model would be most valuable to use in a certain choice situation. The 2-step-model turned out to be valuable on OD-pair 2, which could indicate that this model is the best model to apply on cases with longer travel times and a high number of horizontal curves. However, because of the small number of choice situations in this research no general statements can be concluded.

Furthermore, all models agree on the fact that the last 10 runs t of an individual i in a choice situation c are better predictable than the first 10 runs of the same choice situation c by the same individual i. This gives reason to believe that individuals are indeed exposing more experimental behavior in the beginning of making a certain trip on a frequently base and are exposing more systematic behavior after they have become more familiar with that trip. This concerns less switching behavior as was found in the data-analysis (section 3.3), which makes it easier to predict the route choices for those runs.

In addition, most models are better in predicting driver types containing low levels of switching behavior than driver types containing high levels of switching behavior. On driver type 2 and driver type 4 the 2-step-model performs second-best of all models.

Lastly, the fact that the shortest path theory assuming static expected travel times performs better than the dynamic expected shortest path method (i.e. 1-step-model), indicates that an updating process for expected travel times might be unnecessary. This implies that dynamic route choices can be well predicted using static choice models.

This chapter has shown that the developed 2-step-model is certainly valuable addition to the state-of-the-art route choice models that are currently used. Now, the next chapter will give a quantification of the indifference band using different approaches.

10 Quantification of the indifference band

Quantifying the indifference band is vastly attempted within the research field of route choice behavior. It provides insights in the inertial and switching behavior of individuals in certain choice situations. Therefore, in this research it is also tried to quantify the indifferent band. This is done in three different ways; based on the data-analysis from chapter 3 (elaborated in section 10.1), using the threshold theory from chapter 9 (elaborated in section 10.2) and using the newly developed 2-step-model which is elaborated in section 10.3. Subsequently, the obtained indifference bands are compared to each other in section 10.4. Lastly, section 10.5 discusses the findings and draws conclusions from them.

10.1 Quantification using data-analysis

Part of the data-analysis in chapter 3 examines the indifference band in which there is made a distinction between the conscious and subconscious indifference band. The subconscious indifference band comprises the thresholds of which the individual i is not aware. Therefore, perception errors of individuals are used as an indicator for this subconscious indifference band. Calculation of the subconscious indifference band is based on the observations for which a certain individual i stated that there is no travel time difference between the two route alternatives of a certain OD-pair pq or that a certain route alternative of a certain OD-pair pq was shorter in travel time while according to his experienced travel times on both route alternatives the opposite was the case. The average travel time difference these individuals i have experienced on that specific OD-pair pq during the 20 runs give an indication for their perception error and therewith their subconscious indifference band.

The conscious indifference band comprises the thresholds of which the individual i is aware, for instance because he is satisficing and sticks to a route choice that is good enough while there might exist better choice options. This conscious indifference band is indicated using the observations in which an inertial choice is made. For each individual i on each OD-pair pq the maximum travel time difference (based on experienced travel time) of these inertial choices is determined, representing the indifference band. The results as found in the data-analysis are repeated in table 30 (situation specific) and table 31 (individual specific). A more detailed overview per individual and OD-pair combination can be found in appendix B.1 (subconscious thresholds) and appendix B.2 (conscious thresholds). Note that this data-analysis was performed on all 2065 observations of the dataset.

Table 30: Subconscious and conscious indifference bands per OD-pair pq obtained from data-analysis

OD-pair pq	Subconscious threshold (based on perception errors) [min]*	Conscious threshold (based on observed inertial behavior) [min]*
1	0.48	1.18
2	1.04	1.14
3	1.13	1.51
4	0.37	1.11
5	1.39	1.61
*Average**	0.88	1.31

*In calculating the thresholds, the OD-pair/individual combinations in which no inertial choice is made or perception error is stated, are not included.

**Weighted average based on the number of observations within the dataset per individual i.

Individual i	Subconscious threshold (based on perception errors) [min]*	Conscious threshold (based on observed inertial behavior) [min]*
111	1.37	0.26
112	0.98	1.38
113	0.30	2.04
114	0.97	0.63
115	-	2.11
116	0.61	1.04
121	0.90	1.29
122	0.52	1.14
123	-	1.39
124	-	0.51
125	0.56	1.09
211	-	0.72
212	0.83	1.81
213	-	0.69
214	0.52	1.30
215	0.39	1.04
221	0.32	0.61
222	0.78	1.78
223	1.02	2.08
224	1.16	1.46
225	0.97	1.53
*Average***	0.76	1.22

*In calculating the thresholds, the OD-pair/individual combinations in which no inertial choice is made or perception error is stated, are not included.

**Weighted average based on the number of observations within the dataset per individual i.

10.2 Quantification using the threshold theory

The threshold theory makes use of the inertia thresholds within the observations of the dataset. However, these thresholds are not used as a strict threshold as the experienced travel time must have exceeded this threshold in 100% of the trips remembered by an individual i in order to switch routes. Nonetheless, these model thresholds might provide some insights in the thresholds of switching behavior.

The threshold theory achieved the highest model performance using lower thresholds with a value of μ-0.5σ and upper thresholds of μ+1.0σ for each route alternative, where μ is the mean travel time on that route and σ is the standard deviation of the travel time distribution. In order to find the switching threshold, the upper thresholds are of importance as these are found to be the useful in setting the switching criterion of the threshold theory. The difference between the upper thresholds μ+1.0σ and the mean μ for each route alternative within a certain OD-pair pq is identified as the indifference band per route alternative. After all, it is assumed that one would switch to the other route as this upper threshold is exceeded and therewith has decided that the other route alternative became the better option. As in this research we focused on inertia thresholds, only the thresholds of the longest route alternative are considered. This makes the values more comparable to the values obtained by the data-analysis and the 2-step-model.

Table 32 shows the obtained indifference bands per route alternative and per OD-pair pq. Since this theory uses fixed thresholds, no individual-specific values have been obtained. Note that this threshold theory was performed on only 1193 observations from the available dataset.

Table 32: Indifference bands per OD-pair pq obtained from threshold theory

OD-pair pq	Route	Mean μ [min]	Std σ [min] (indifference band per route alternative)	Upper threshold μ+1.0σ [min]	Indifference band per OD-pair pq[min]
1	1	8.22	1.28	9.50	1.80
	2	8.72	1.80	10.52	
2	3	14.94	1.34	16.28	1.31
	4	16.91	1.31	18.22	
3	5	7.69	0.92	8.61	1.08
	6	9.15	1.08	10.23	
4	7	9.87	1.27	11.14	1.27
	8	9.82	1.03	10.85	
5	9	10.45	0.93	11.68	0.93
	10	7.94	1.06	9.00	
*Average**		10.24	1.22	11.47	1.29

*Weighted average to the amount of choices for the specific route alternatives.

10.3 Quantification using the 2-step-model

The 2-step-model can provide insights in the indifference band using the sub-models of the combined model. As the main interest is on the inertia thresholds only the inertia model is used. Remember from chapter 4 that this model provides a probability p that a certain individual i will make an inertial choice in choice situation c. In general, it can be assumed that the turning point at which an individual i changes his choice behavior from sticking to his current route choice to switching to the other route alternative will occur when this probability p is 50%. After all, at a probability p lower than 50%, it is more likely that an individual i will make a switching choice, while at a probability p higher than 50% it is more likely that this individual i will stick to his current route choice. The indifference band can now be found by identifying the value of the model's attribute related to travel time (i.e. the attribute 'Δtt$_{prev}$' in the inertia model) at which this turning point of probability p being 50% is predicted for a certain individual i at OD-pair pq, keeping all other attributes at their original value as given by the dataset as these attribute values do not change for a certain individual and OD-pair combination. This value of the travel time attribute represents the travel time difference between both route alternatives that is needed for individual i in choice situation c in order to switch routes. The resulting indifference bands per OD-pair pq can be found in table 33 and the indifference bands per individual i can be found in table 34. A more detailed overview per individual and OD-pair combination can be found in appendix D. Note that this 2-step-method was performed on only 1193 observations from the available dataset.

Table 33: Indifference bands per OD-pair pq obtained from 2-step-model

OD-pair pq	Average inertia thresholds [min]*
1	1.55
2	2.55
3	1.44
4	1.40
5	1.11
*Average***	1.67

*In calculating the average thresholds, the OD-pair/individual combinations in which no data was available are not included.

** Weighted average.

Table 34: Indifference bands per individual *i* obtained from 2-step-model

Individual *i*	Average inertia thresholds [min]*
111	0.10
112	1.25
113	3.02
114	0.45
115	-
116	2.76
121	0**
122	10.77
123	1.98
124	0**
125	1.17
211	2.45
212	0.84
213	-
214	3.17
215	1.41
221	1.30
222	-
223	4.95
224	1.71
225	0**
*Average***	2.27

*In calculating the average thresholds, the OD-pair/individual combinations in which no data was available are not included.

**The probability p stays below 50%, even at a travel time difference of 0. Therefore, the indifference band is set at 0.

*** Weighted average.

10.4 Comparison of obtained indifference bands

Figure 45 visualizes the individual-specific indifference bands found by the data-analysis (conscious and subconscious indifference bands) and 2-step-model (conscious indifference bands). In general, the 2-step-model found relatively high indifference bands compared to the indifference bands found by the data-analysis. An explanation for this may lie in the fact that the indifference bands found by the 2-step-model are based on all observations in which an inertial choice is possible, while the indifference bands found in the data-analysis are based on only those observations in which an inertial choice is actually made or an individual actually stated that he was indifferent for the travel time difference between the two route alternatives. Note that especially the conscious indifference band of individual 122 (and to a lesser extend individual 223) obtained by the 2-step-model is very high. One could consider these to be outliers. They occur because the coefficients of the inertia sub-model are estimated for all individuals together. In combination with the characteristics of this individual 122 (or individual 223) somewhat extreme results are obtained. Remark that these high values are not obtained by the data-analysis for these specific individuals. That might be the case since within the modeled expected travel times on which the inertia thresholds in this data-analysis are based simply do not contain these big differences. As a result this analysis obtained only threshold minimums; when more runs are made, higher thresholds might be obtained. A closer look at these individuals within the dataset shows that they first try both route alternatives and after that stick to their preferred route alternative without making any switches during the remaining experimental runs. So, these individuals have developed a strong preference for a certain route alternative (i.e. they belong strongly to driver type 2). If this is the longer route alternative for some OD-pairs, this results in a high likelihood of this individual to perform inertial behavior leading to a high inertia threshold. It is likely that in a total population, individuals exposing this behavior are more common. Therefore, it is chosen to keep these values within this research.

Furthermore, it seems that the subconscious indifference band is found to be the lowest for most individuals, as was expected in section 2.1.7.
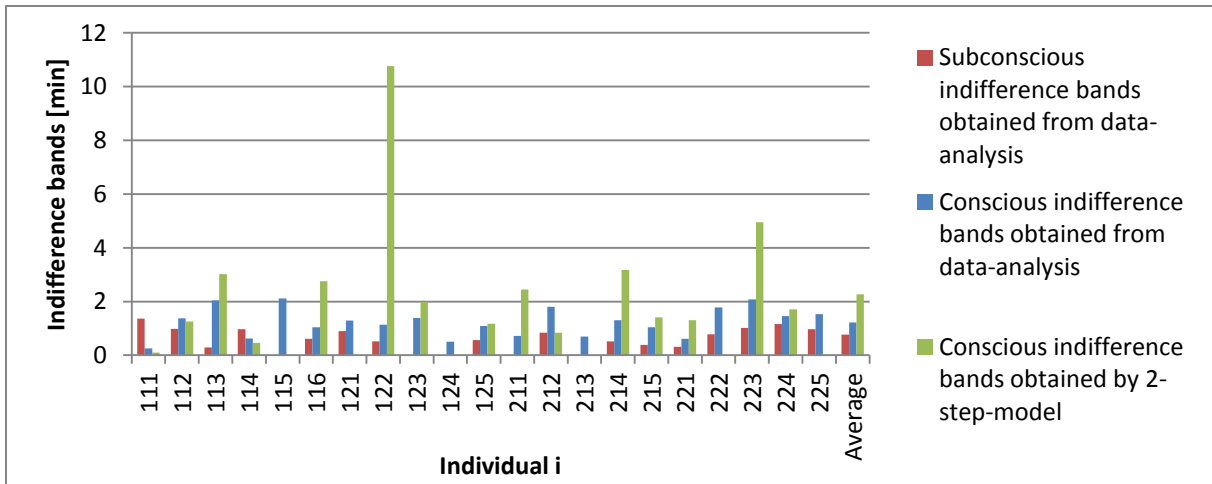
Figure 45: Comparison of the individual-specific indifference bands per individual i

Figure 46 shows the situation-specific indifference bands found by the data-analysis (subconscious and conscious indifference bands), the fixed threshold model (conscious indifference bands) and the 2-step-model (conscious indifference bands). The averages of the found indifference bands are more close to each other than those for the individual-specific thresholds. The subconscious indifference band is on average again the smallest of all four measures, while the indifference bands found by the 2-step-model are again on average the highest. Note that the high value obtained by the 2-step-model on OD-pair 2 is a result of, among others, the high indifference band of individuals 122 and 223.

As mentioned earlier, the different results found by the different approaches can be explained by the (number of) observations that are used in order to indicate the value of the indifference band. In addition, the fixed threshold theory uses a threshold value of 1σ for all OD-pairs pq and individuals i, while on a more detailed level the threshold values might significantly vary. Setting these values per individual i might obtain more accurate values, although the current results are quite similar in order of magnitude to the found values using the other approaches.
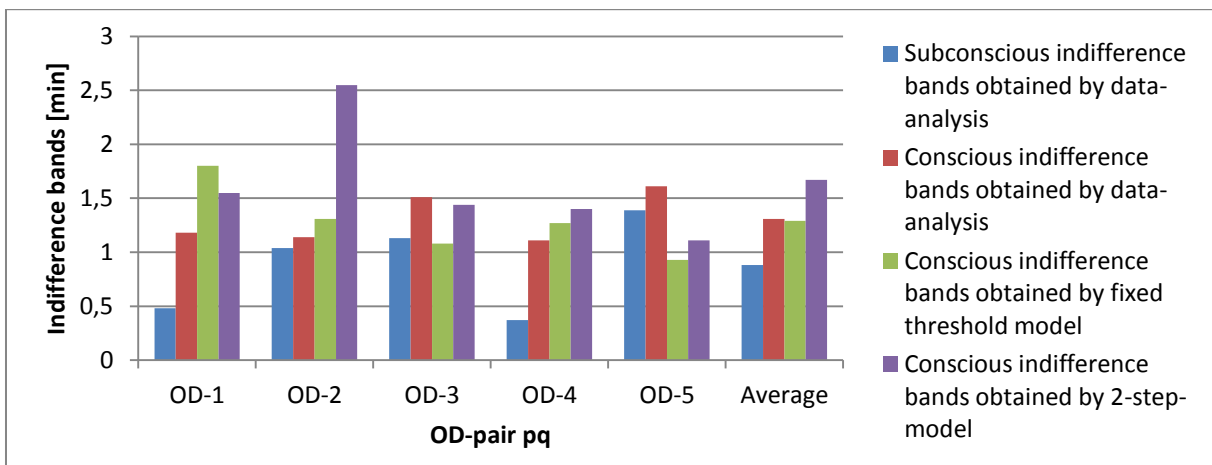
Figure 46: Comparison of the situation-specific indifference bands per OD-pair pq

None of the three quantification methods obtained the exact value of the indifference band. The data-analysis only uses information on individuals that stated to be indifferent or observations at which an actual inertial choice is made, the threshold theory assumes that the thresholds are the same for all individuals and are fixed over time and the inertia model is based on attributes that

seem to be explanatory for inertial behavior although the model fit is not perfect. Therefore, all three methods will have some errors in quantifying the indifference band. Over all, it can be assumed that they all provide reasonable indications of the indifference band and the real value lies somewhere in between.

In order to make the obtained threshold values more workable and more easily comparable to other situations, they are translated to percentages of the average trip travel time (shown in table 35). It is found that the situation-specific conscious indifference band is about 12.6%-16.3% of the average total travel time of a certain trip, while the individual-specific conscious indifference band is about 12.1%-22.6% of the average total travel time. The subconscious indifference band is 8.7% of the average total travel time for the situation-specific point of view and 7.5% of the average total travel time for the individual-specific point of view.

Table 35: The indifference band expressed as percentage of the average trip travel time

OD-pair pq	Average travel time and travel time difference of OD-pair pq [min]*	Subconscious indifference band – Data-analysis		Conscious indifference band – Data-analysis		Average travel time and travel time difference of OD-pair pq [min]**	Conscious indifference band – Fixed Threshold Theory		Conscious indifference band – 2-step-model	
		Absolute [min]	Relative [%]	Absolute [min]	Relative [%]		Absolute [min]	Relative [%]	Absolute [min]	Relative [%]
1	8.45 (0.1)	0.48	5.7	1.18	14.0	8.59 (0.5)	1.80	21.0	1.55	18.0
2	15.77 (1.5)	1.04	6.6	1.14	7.2	15.61 (2.0)	1.31	8.4	2.55	16.3
3	8.19 (1.6)	1.13	13.8	1.51	18.4	8.04 (1.5)	1.08	13.4	1.44	17.9
4	9.70 (0.6)	0.37	3.8	1.11	11.4	9.83 (0.1)	1.27	12.9	1.40	14.2
5	8.28 (2.5)	1.39	16.8	1.61	19.4	8.25 (2.5)	0.93	11.3	1.11	13.5
Average	10.08	0.88	8.7	1.31	13.0	10.24	1.29	12.6	1.61	16.3
Correlations average TT ***		0.06		-0.53			0.11		0.94	
Correlations Δ TT ****		0.95		0.79			-0.64		0.15	
Individual i		Absolute [min]	Relative [%]	Absolute [min]	Relative [%]		Absolute [min]	Relative [%]	Absolute [min]	Relative [%]
Average	10.08	0.76	7.5	1.22	12.1	10.24	-	-	2.27	22.1

*Weighted average of the travel time on the two route alternatives, based on the 2065 observations
** Weighted average of the travel time on the two route alternatives, based on the 1193 observations
*** Correlation between absolute indifference band and the average travel time per OD-pair pq
**** Correlation between absolute indifference band and the difference in travel time per OD-pair pq

The correlations of the absolute indifference bands with the average travel time per OD-pair pq and the difference in average travel time per OD-pair pq are calculated for each quantification method. It can be seen that the results of the 2-step-model are highly correlated to the average travel time of a trip, which means that if the average travel time of a trip increases, the indifference band also increases. On the contrary, there is a very low correlation with the travel time difference. For the other quantification methods, low correlations to the average trip travel times are found, while high correlations to the travel time differences are identified. Note that the results of the conscious indifference band obtained from data-analysis and the threshold theory have a negative correlation to the average trip travel time and the travel time difference respectively. This indicates that if the average travel time of a trip or the difference in travel time increases, the indifference band decreases.

Overall, it seems that the data-analysis quantification methods provides indifference bands that are correlated to the travel time difference between the two route alternatives of a certain OD-pair pq, while the 2-step-model provides indifference bands that are correlated to the average travel time of a certain OD-pair pq. This might be due to the used principle of each method. For example, the data-

analysis used travel time differences in order to determine the indifference band. Therefore the finding of a high correlation with the travel time differences is not that surprising. In addition, the 2-step-model uses different attributes in order to determine the inertia threshold. The estimates of these attributes result in switching points that apparently follow the average trip travel times of the different choice situations.

10.5 Discussion and conclusion

The findings indicate the inertia thresholds to be on average between 1.22 minutes and 2.27 minutes, corresponding to 12.1%-22.1% of the total trip travel time. However, the width of the indifference band is highly dependent on the characteristics of both the choice situation c and the individual i. In this research the indifference band is quantified based on 5 different choice situations c and 21 individuals[5]. These numbers might be small for quantifying the indifference band. Nonetheless, the 21 individuals are assumed to represent the population in the Blacksburg area well, as individuals are recruited over a long range of ages and the amount of male and female is set equally. The five different trips, however, are all relatively small with an average travel time of 10.08 minutes and an average distance of 7.7 km. One can imagine that different widths for the indifference band would be found if, for instance, the trips take ~45 minutes and cover distances of ~40 km. The expression of the findings in percentages of the average trip travel time might account for this issue.

In literature, a (subconscious) perception threshold of 3 á 4 minutes (23%-31% of trip travel time) is found by Vreeswijk et al. (2013a), which is significantly higher than the subconscious threshold of 0.88 minutes (situation-specific, 8.7% of trip travel time) and 0.76 minutes (individual-specific, 7.5% of trip travel time) found in this research. A reason for this might be the fact that the identified perception thresholds in this research are only indications, since no quantifiable perceptions were available from the dataset. However, these are not included in this analysis as it is not possible to assess their perception error based on the available data. In addition, (Vreeswijk et al., n.d.) found conscious satisficing thresholds of on average 1.18 and 1.34 minutes, which are lower than their found subconscious thresholds and the conscious thresholds between 1.22 minutes and 2.27 minutes found in this research using the same dataset.

Srinivasan and Mahmassani (1999) found evidence for route switching indifference bands of 3.44 and 4.14 minutes, corresponding to 17%-22% of the total travel time of a certain trip. In addition, Mahmassani and Liu (1999) found an average relative indifference band of about 19% for pre-trip route switching. These percentages are comparable with the relative indifference bands found in this research (12.1%-22.1%).

Since the width of the indifference band highly varies for each situation-individual combination the found values should be regarded as an indicative measure rather than a conclusive one. The different findings in literature suggest that there is no deterministic indifference band that fits all situations and all individuals. Therefore, it can only serve as a reference and outline the magnitude of the inertia thresholds when used in the field of route choice modeling and traffic management research. However, as for most practical applications it is not possible to distinguish between each individual driver, an indicative measure of the indifference band might be sufficient.

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[5] Note that not for every situation-individual combination a value could be obtained.

11 Conclusions, discussions and recommendations

This chapter will discuss the main conclusions of this research by answering the main research question of this research (section 11.1). Subsequently, spin-off conclusions found in this research are presented (section 11.2). This is followed by an elaboration on the research implications that the findings and conclusions involve (section 11.3). Lastly, this chapter will conclude with a number of recommendations and directions for future research (section 11.4).

11.1 Main conclusions

The objective of this research was to develop and evaluate a route choice model based on the notions of inertia and the indifference band in order to improve predictions on daily route choices of individuals and to quantify the indifference band. The focus of the research was on pre-trip route choices under day-to-day dynamics for the next day that a certain trip will be made. The four choice strategies as identified by Vreeswijk et al. (n.d.) were used as a starting point. In order to achieve the objective the following main research question was formulated:

How and to what extent can day-to-day route choice modeling be improved by incorporating the principles of inertial behavior in order to predict route choice behavior accurately and quantify the inertia related indifference band?

This research question can be broken down into three parts; (1) How to improve day-to-day route choice modeling by incorporating the principles of inertial behavior, (2) to what extent will the day-to-day route choice modeling be improved and (3) what is the value for the inertia related indifference band according to these incorporated principles of inertial behavior. Conclusions will be made on all three parts.

11.1.1 'How' (1)

First the answer to the 'How'-part of the question is elaborated. A day-to-day route choice model is developed by incorporating the principles of inertial behavior using data obtained in a real-world experiment. In order to do so, observed choice behavior was categorized into four groups of choice strategies; minimizing (by switching), minimizing (by non-switching), inertial choice making and compromising. Data-analysis showed that inertial behavior and the magnitude of both the conscious inertia threshold and subconscious perception threshold might be best explained using individual-dependent variables and situation-dependent variables as high variations within the findings are identified for the different individuals and OD-pairs.

Findings in literature emphasize the above mentioned finding indicating that inertial choices can be explained by travel time differences between route alternatives, average travel speeds and distance as well as factors related to the simplicity of routes. In addition, familiarity and previous experiences with the route alternatives are found to influence the decision to switch routes or not. Pleasure, delay and income are also found to be important in route switching decisions. Furthermore, it was found in literature that a route choice model should include a mechanism that is based on the expected performance of the route alternatives.

Regression analysis examining six different approaches in order to account for the principles of inertia, showed that a combined modeling approach, consisting of a sub-model that predicts inertial

choices in situations that this choice strategy could be exposed and a sub-model that predicts compromising choices in situations that that choice strategy could be exposed (as both behaviors are mutually exclusive), would be the best. The obtained regression models of this combined approach indicate that individual characteristics and characteristics of the choice situations where most important in explaining exposed choice strategies such as inertia, while variables on experience were found to be less important. This combined model was then implemented in a 2-step modeling framework consisting of a Dynamic Expected Shortest Path Module and a Choice Strategy Module. The first module determines a preliminary choice based on a travel time updating process and the second module alters this preliminary choice based on the choice strategy predicted by the combined regression model. It is believed that this modeling framework offers a good and simple starting point for incorporating the principles of inertial behavior into a route choice model.

In order to extend the 2-step-model to an agent-based approach using the Bayesian sampling method in combination with the Cholesky Decomposition tool accounting for parameter correlations within the model parameters, this model performs comparable to the initial 2-step-model with a model performance of 74.55%. When looking at the different OD-pairs pq and runs t, a similar trend is found in performance is found. That is, when the initial 2-step-model has a high performance on a certain OD-pair and lower on the next OD-pair, the agent-based 2-step-model has also a high performance on that specific OD-pair and a lower on the next OD-pair. This makes this agent-based approach very suitable for micro-simulation studies.

Discussion

The experimental set-up results in some limitations to the dataset which may have caused some observations to not be completely reality alike. These are already elaborated upon in section 3.1 and therefore only briefly repeated in this discussion. First of all, there was no control over the traffic conditions and actual travel times, and during every run the participants completed five trips consecutively without arrival time pressure which is often not the case in reality. These issues might have affected the route choice behavior that individuals would have exposed in daily life. Furthermore, the perceptions of individuals are only obtained prior and posterior to the experiment and therefore highly aggregated.

In addition to these limitations, only five different OD-pairs with only two different route alternatives and only 20 different individuals were used for the experiment, which is low compared to other studies but understandable with respect to the effort and time consumption of each experimental run and certain budget constraints. Most other studies are based on stated preference questionnaires, which makes it easier to capture a higher number of OD-pairs, route alternatives and individuals. Nonetheless, these studies have their own limitations as they have often not much observations per individual and per OD-pair and are less reality alike than observations from this real-world experiment.

In addition, only 20 runs are obtained for each individual on each OD-pair. Based on the finding that different choice patterns have established and the likeliness that an individual would need a long period of time before his choice pattern transforms in one of the other choice patterns (which might be more likely to be a result of a change in the road network characteristics or conditions than individual characteristics), it can be stated that the number of 20 runs were sufficient for the purpose

of this research. It is believed that a few additional runs would not result in other choice patterns, although more observations in general could be useful. That is because from the obtained 2065 observations only 1193 turned out to be useful as experience on both route alternatives by each individual was required. This resulted in the available dataset to be quite small.

Furthermore, the experiment was executed in the Blacksburg area, which is a college town within an area with low population density and low congestion. As a result, the research findings might be different if data obtained in a highly populated or congested area, such as a metropolis, was used. This all together makes that the results and conclusions of this research are usable but should be interpreted with care.

The regression models are developed with care. However, the obtained model is very sensitive to the variables that are used as input for the stepwise regression. Therefore, different regression models were found with a difference in explanatory power of only 0.01 (R^2). In this research the model with the highest explanatory power is chosen. However, the model with the slightly lower explanatory power might perform just as well or even better in terms of correctly predicted route choices. In addition, a finite number of variables are considered to be relevant in explaining the choice strategies as they were found in literature and the data-analysis. It might be the case that there exist other explanatory variables that are not included in this research, either because their importance on route choice behavior is not acknowledged at the moment or data about these variables were not available within the dataset.

The 2-step-model assumes a initial expected travel time which consists of the average travel time on a certain route during the specific peak hour. As a smoothing factor α of 0.01 is found to achieve the highest model performance, the initial expected travel time becomes crucially in determining and updating the expected travel times for the different route alternatives. However, individuals might have already a certain perception error for the travel time at the beginning of their runs and therefore do not expect the average travel time of the specific time of day. Therefore, the determination of the initial expected travel time might be not reality alike and need to be reconsidered. A possibility might be to assume the initial expected travel time to be stochastic, randomly picking this from some distribution around the average travel time of a certain route for each individual.

In addition, the 2-step-model is only applicable if the decision maker has only two route alternatives to choose from. In real-world route choices, more than two route alternatives might be available to the decision maker. Therefore, the number of alternatives first needs to be reduced to two. As Li, Guensler, and Ogle (2005) found that 96.7% of commuters use only two routes on a routinely basis (i.e. use a certain route more than twice within 10 days) for their daily trips, one can imagine that it might be possible to reduce the considered route alternatives using certain algorithms. An example might be found in the if-then search rules used within the SILK-theory as proposed by Zhang (2006a).

Furthermore, both sub-models of the combined model contain the attribute 'Maximum familiarity' which is obtained prior to the experimental runs. One can imagine that after a few experimental runs individuals become more familiar with the route alternatives. Therefore, updating the familiarity of

individuals with certain routes might make the route choice model more reality alike. Again, research might be necessary in how to update this attribute.

In order to extend the 2-step-model to an agent-based approach using the Bayesian sampling method in combination with the Cholesky Decomposition tool provides reasonably comparable results as the initial 2-step-model. Therefore, this would be a very suitable way to use the model within micro-simulation studies. However, in order to execute Bayesian sampling on a different demographic area, a dataset specific for that area is needed, including observed choices (or choice strategies). Otherwise, the posterior distribution cannot be found. This might be a disadvantage of the method application, although this data might be easily obtained using stated preference questionnaires, which save time and budget compared to real-world experiments. Besides, the used dataset in this research might be representative for multiple areas within Virginia or even the United States. In that case no additional data is necessary.

11.1.2 'To what extent' (2)

Now the answer to the 'To what extent'-part of the research question is elaborated. The sensitivity analysis shows that the 2-step-model is not very robust as the model is sensitive to changes, and therewith to errors, in 9 out of 13 factors. The model is most sensitive to changes in the constants and the personality traits. Changes in the travel time attributes do not seem to affect the model performance much, although they are often considered to be most important in route choices.

The 2-step-model provides correct predictions in 75.35% of the cases. This places it among the state-of-the-art models with the highest performances. In addition, its lowest performance on the different OD-pairs pq is the second-highest compared to the lowest performances of the state-of-the-art models. This indicates that this model has one of the most constant performances when applied on different choice situations. In addition, the 2-step-model has the highest performance on OD-pair 2, which is a relatively longer trip with a lot of horizontal curves. This might indicate that the 2-step-model can improve route choice modeling specifically on choice situations of this kind. Furthermore, the 2-step-model performs second-best of the state-of-the-art models in predictions on daily route choices for driver type 2 and driver type 4. This might indicate that the 2-step-model would especially be valuable in predicting route choices made by these driver types.

Discussion

For comparison of the 2-step-model with other state-of-the-art models all models are applied on the same dataset, namely the dataset of Tawfik. However, the 2-step-model is developed using the same data. Although the model coefficients are assumed to be valid after the cross-validation in chapter 6, one can argue if this might bias the comparison of the model performances. Besides, some adaptations had to be made to the state-of-the-art models in order to apply them to the available dataset. This might affect the model performance of the concerned models. In general, it is tried to implement all the models as well as possible.

11.1.3 'Inertia related indifference band' (3)

Lastly, the answers to the 'inertia related indifference band'-part of the research question is elaborated. In order to quantify the inertia threshold based on the 2-step-model, the inertia sub-model applied in the second step of the model is used. This inertia sub-model provides a probability p that a certain individual i will make an inertial choice in choice situation c. It is assumed that the

turning point at which an individual i changes his choice behavior from sticking to his current route choice to switching to the other route alternative will occur when this probability p is 50%. The indifference band can now be found by identifying the value of the model's attribute related to travel time (i.e. the attribute 'Δtt_{prev}') at which this turning point of probability p being 50% is predicted for a certain individual i at OD-pair pq. This resulted in an average situation-specific inertia threshold of 1.67 minutes (16.3% of the average trip travel time) and an average individual-specific inertia threshold of 2.27 minutes (22.1% of the average trip travel time).

Two other methods are used for quantifying the indifference band; the data-analysis and the threshold theory. Although the 2-step-model provides in general higher thresholds than those obtained by the data-analysis and threshold theory, they all found the same order of magnitude (situation-specific: 1.67, 1.31, and 1.29 minutes respectively, individual-specific: 2.27 and 1.22 minutes respectively (no individual-specific result for threshold theory)). Overall, inertia thresholds between 12.1% and 22.1% of the average trip travel time are found on an individual level, using the OD-pair point of view inertia thresholds between 12.6% and 16.3% of the average trip travel time are obtained. In addition, it seems that subconscious indifference bands based on perception errors (7.5%-8.7% of the average trip travel time) are in general lower than conscious thresholds based on inertial behavior.

Discussion

The width of the indifference band is highly dependent on the characteristics of both the choice situation c and the individual i. In this research the indifference band is quantified based on 5 different choice situations c and 21 individuals. These numbers might be small for quantifying the indifference band. Nonetheless, it is assumed that these individuals give a good representation of the population of the Blacksburg area. In addition, the five different trips are all relatively small with an average travel time of 10.08 minutes and an average distance of 7.7 km. Therefore, it might be the case that the found indifference bands are not representative for longer trips or in other areas. However, the found percentages of the average trip travel time are comparable to those found in other researches (e.g. (Mahmassani & Liu, 1999; Srinivasan & Mahmassani, 1999; Vreeswijk et al., 2013a)).

11.2 Spin-off conclusions

- All state-of-the-art models showed a lower performance on the first 10 runs than on the last 10 runs of each trip made by the individuals. This underlines the believe that individuals expose more experimental behavior the first few times they are making a certain trip, but as they become more familiar with it, more systematic and therewith more predictable behavior is exposed.
- When model performances are detailed for every OD-pair pq, it is found that certain state-of-the-art models perform better on certain OD-pairs than others and vice versa. This indicates that in certain circumstances or choice situations a certain route choice model would be the best to use, leaving the implication that a hybrid model using different choice models for different choice situations could significantly improve current modeling practice.
- When model performances are detailed for the four different driver types d, it is found that most state-of-the-art models perform best on driver types with a low level of switching behavior, while a higher level of switching behavior leads to lower model performances. Nevertheless, valuable models for each driver type could be identified. Therefore, a hybrid

model using different models for different driver types d has also potential to improve current modeling practice.

- The model performance of the prospect theory and, to a lesser extent, the regret theory suggests that these choice models might not be that suitable in predicting day-to-day route choices. Although on some OD-pairs they are among the best performing models, on other OD-pairs they perform dramatically low. Overall, the regret theory performs very low with only 43.17%, while the regret theory performs better with 65.88% correctly predicted route choices. On the contrary, the threshold theory performed very well in predicting route choices as one of the models specifically based on the principles of route choice behavior. Particularly, since it was designed capturing long-term route switching instead of day-to-day dynamics and the number of available observations was therefore lower than preferred.

- Comparing the overall performance of the dynamic 1-step-model (71.76%) with the overall performance of the static shortest path model (75.76%) indicates that including a dynamic updating process for the expectations of a certain individual for the different route alternatives might be unnecessary. This is opposed to what was found in literature, stating that a route choice model should include a mechanism that is based on the expected performance of the route alternatives. Apparently, day-to-day dynamics in route choices can be well accounted for using a static choice model.

- Based on the agent-based 2-step-model it is found that ignoring parameter correlations when simulating individuals results in a model performance that is similar to the model performance of a random prediction process. Accounting for parameter correlations increases the performance of the agent-based model by approximately 25% point, emphasizing the importance of these parameter correlations. So it can be concluded that in explaining route choice behavior the explanatory variables are strongly correlated which is crucial in obtaining accurate model results and makes day-to-day route choice modeling therefore very complex.

11.3 Research implications

The findings in this research might have some implications for the current modeling practice. First of all, data-analysis showed that inertial behavior could be identified within the real-world choice behavior in 23% of the cases leading to lost travel time per individual per trip of around 1 minute, emphasizing the importance of (non-)switching behavior in route choice modeling. In total, 1/3 of all choices contained a suboptimal choice in terms of travel time (i.e. inertial choices (23%) + compromising choices (10%)). Apparently, individuals do not necessarily (want to) use the optimal travel time alternative. This emphasizes the potential of management measures pushing individuals into a certain suboptimal choice direction in order to establish a system optimum in the road network.

In addition, this research showed the importance of individual characteristics, especially the personality traits, on this (non-)switching behavior. Until now, the main considerations in route choice models focused on the characteristics of the different route alternatives, like travel time. More attention to this facet of individual characteristics and insights in the four identified choice strategies (including inertia) might be useful to include in current modeling practice.

A question that rises is whether approximately 75% correctly predicted cases by the 2-step-model is useful for application in practice. For application on a daily and individual level it is desired to approach reality as close as possible and a model performance of about 75% might therefore still be low. However, when traffic flows are the main interest of the application a wrong predicted choice of an individual on one route might be compensated by a wrong predicted choice of another individual on the other route and therewith approach a reality alike traffic flow more closely than the provided model performance of 75% in this research. As the commonly used modeling approach of the shortest path theory obtains also a model performance of 75% which is according to other researches relatively high (see discussion in chapter 9), it can be assumed that a model obtaining 75% correctly predicted cases is sufficient to be useful in practice.

Despite the good performance of the 2-step-model compared to the other models, the question remains whether the model has the potential to be used in the common route choice modeling practice. The vastly applied shortest path theory provides a slightly higher performance then the 2-step-model when applied on the used dataset in this research. In fact, this shortest path theory outperforms all state-of-the-art models except the threshold theory. In addition, this modeling approach is quite straightforward and simple, and does not need any specific data besides the average travel times on the different route alternatives, such as individual characteristics of the population. Therefore, it is believed that in the near future this commonly used modeling approach will remain preferred over the newly developed 2-step-model. In addition, the quite recently developed threshold theory outperformed the commonly used shortest path theory. However, more feeling and insights in this model and its application is necessary in order to be used in practice. Therefore, it is believed that the shortest path theory will remain preferred over this threshold model as well.

Research findings related to the model performances of the different state-of-the-art model and the developed 2-step-model provide useful insights in the different choice situations and different driver types for which these different models are well applicable. These insights might be valuable for the modeling practice in the future, although they are very preliminary at the moment. However, the results and findings provide sufficient reason for further examination that might lead to more concrete findings in the future. Possibly, they change the current modeling practice using each state-of-the-art model more case-specific and therewith increase the prediction accuracy.

Research findings related to the indifference band show that the indifference band highly varies for each situation-individual combination and that none of the three used quantification methods obtains the exact value of the indifference band. The different findings suggest that there is no deterministic indifference band that fits all situations and all individuals. Therefore, the found values should be regarded as an indicative measure rather than a conclusive one and it can only serve as a reference and outline the magnitude of the inertia thresholds when used in the field of route choice modeling and traffic management research. However, since for most practical applications it is not possible to distinguish between each individual driver, an indicative measure of the indifference band might be sufficient.

Measures within traffic management often aim at improving the throughput in a road network by adjusting traffic flows and therewith influencing individual's route choices. The found indifference bands of 12% to 22% of the trip travel time indicate that a significant improvement or deterioration of the traffic state or route characteristics on one of the available route alternatives would be necessary before individuals will change their route choice. It is assumed that providing travel time information will decrease perception errors of individuals and therewith reduce their indifference band. As a result, smaller changes in route characteristics and the traffic state will already effectively influence individual's route choice behavior. Perception indifference bands are believed to be around 8%-9% of the trip travel time, which accounts for about half to two-third of the total indifference band. However, besides eliminating perception errors and therewith lowering the indifference bands, these findings can also be used to reroute individuals and push traffic flows towards a system optimal state. After all, these indifference bands indicate the time margin in which an individual is not aware of the travel time differences or is just not interested in this difference. Therefore it is likely that individuals would accept travel information that directs them towards a particular suboptimal route that lies within these time boundaries. Providing travel information might therefore be an important (additional) measure to improve the throughput in a road network.

11.4 Future research

This extensive research on modeling daily route choice behavior incorporating the principles of inertial behavior and corresponding inertia thresholds provided several important findings. In addition, this research has thrown up a few questions in need of further investigation.

- Currently, the 2-step-model performs quite well compared to other models. However, there might be some room left for improvements.
  - First of all, some further examination of the travel time updating process might be useful. In this research an averaging method and smoothing method is used. The smoothing method led to better results although there are some indications suggesting that a travel time updating method is not beneficial. It is suggested to replace the first step of the model by the utility maximization theory based on travel time, as it is found reasonable to believe that a combination of these models might lead to a model performance that exceeds their current performances.
  - In addition, the determination of the initial expected travel time can use some further examination. Currently, the average travel time on the route alternatives experienced by all individuals broken down by time of day is used as initial expected travel time. However, significant differences are found when the general average travel time is used (i.e. not broken down by time of day). A suggestion might be to assume a stochastic initial expected travel time, randomly picking this from some distribution around the average travel time of a certain route for each individual i.
- It is recommended to apply the state-of-the-art models and the 2-step-model on other datasets in order to gain some more insights on the model performances in different choice situations. Eventually, it might be possible to determine from these insights which model would be in general the best model to apply in a certain situation, leading towards the development of a hybrid model as mentioned in the previous section. In addition, more insights in the driver types d and which models might be valuable to use for choice predictions for these different types could be gained as well. The findings on both the choice situations and driver types can be combined into one hybrid model, indicating which model

to use if a certain individual i exposes choice behavior of a certain driver type d at a certain choice situation c.

- As the 2-step-model can only be applied in choice situations with two route alternatives, it should be examined how to reduce the multiple route alternatives that are available for OD-pairs in most road networks to only two route alternatives.
- The introduction of this research (chapter 1) mentioned that the experiment that resulted in the used dataset for this research is currently being repeated, adding the providing of travel time information to the participants to the experimental set-up. As travel time information is expected to affect drivers' perception and route choice behavior, it is interesting to study how this travel information affects the findings presented in this research using the dataset of the repeated experiment. For instance, a variable on travel information can be included to the sub-models of the combined. After recalibration, the change in coefficients indicates the effect of providing travel time information on the model.
- Finally, if the model is improved and further investigation is conducted, the 2-step-model can be implemented in micro-simulation studies, assigning simulated individuals to a simulated road network according to the route choice predictions of the 2-step-model. This can also provide insights in the effects of implementing the model with and without travel time information on the road network.

Over all, the findings, conclusions and recommendations for future research underline the importance and relevance of this research as stated in the introduction of this research (chapter 1). The developed model provides an initial starting point for further improvements in route choice modeling. The conclusions and recommendations show some interesting findings that provide direction to further improvements of the modeling practice, such as the development of a hybrid model based on OD-pair or driver type and the importance of the travel time updating process and the used initializations. The model can be used in simulation research in order to analyze certain proposed management measures based on day-to-day dynamics or, for instance, adapt the settings of advanced traffic light installations based on the model predictions for the next day. In addition, a better understanding of the principles of inertial behavior and daily route choice behavior of individuals in general is obtained, which can be used as a foundation for research on the effects of travel information on route choice behavior. Findings on the indifference band give an indication to what extent individuals can be pushed into a certain direction in order to realize a more optimal use of the transportation network.

12 Bibliography

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13 Appendices

This chapter provides the appendices that are referred to in the report. Appendix A contains examples of the if-then rules related to the SILK theory. Appendix B shows the detailed indifference bands per individual and OD-pair combination for the subconscious and conscious indifference bands obtained from data-analysis. Appendix C contains an analysis of the sampler output of the MCMC sampler algorithm used for the Bayesian approach in order to obtain an agent-based 2-step-model. Appendix D shows the detailed conscious indifference band per individual and OD-pair combination obtained from the 2-step-model.

Appendix A; If-then rules – SILK theory

Route alternative for consideration

Below, if-then rules are stated that replicate the heuristics individuals use to identify alternative routes based on spatial knowledge of the individual.

Choose Route A as the alternative route for consideration, if

[ΔTime = (0.21 ~ infinity)]	Rule 1
Or [ΔTime = (0.13 ~ 0.21)	
And ΔBtime = (–infinity ~ –0.57)]	Rule 2
And ΔBtime = (–0.57 ~ 0.19) And ΔTransfer = 0 or 1]	Rule 3
And Time = (30 minutes ~ infinity)]	Rule 4
And ΔBtime = (0.19 ~ infinity) And ΔTransfer = 1]	Rule 5
Or [ΔTime = (0.04 ~ 0.13)	
And ΔBtime = (–infinity ~ –0.57)]	Rule 6
And ΔBtime = (–0.57 ~ 0.19) And (ΔTransfer = 0 or 1)]	Rule 7
And ΔBtime = (–0.57 ~ –0.19) And (Time = (15 ~ 30 minutes)]	Rule 8
And ΔBtime = (0.19 ~ 0.57) And (ΔTransfer = 1)]	Rule 9
Or [ΔTime = (–0.04 ~ 0.04)	
And ΔBtime = (–infinity ~ –0.57)]	Rule 10
And ΔBtime = (–0.57 ~ 0.19) And ΔTransfer = 1]	Rule 11
And ΔBtime = (–0.57 ~ –0.19) And (ΔTransfer = 0)]	Rule 12
And ΔBtime = (0.19 ~ 0.57) And (ΔTransfer = 1)]	
Or [ΔTime = (–0.21 ~ –0.04)	
And ΔBtime = (–infinity ~ –0.57)]	Rule 13
And ΔBtime = (–0.57 ~ 0.19) And (ΔTransfer = 1)]	Rule 14
And ΔBtime = (–0.57 ~ –0.19) And (ΔTransfer = 0)]	Rule 15
Otherwise, choose Route B as the alternative route for consideration.	Rule 16

Route changing rules

Below, if-then rules are stated that replicate the heuristics individuals use to (not) switch routes.

Change route, if

[ΔTime ≤ -39%]	Rule 1
or [ΔTime ≤ -11% and ΔPleasure ≥ -1]	Rule 2
or [ΔFamiliarity ≥ 3 and Commute time ≤ 20 min]	Rule 3
or [ΔTime ≤ 6% and ΔPleasure ≥ 3]	Rule 4
or [ΔTime ≤ 15% and Δ Familiarity ≥ 2 and ΔDelay ≥ -40%]	Rule 5
or [Familiarity = 1 and ΔTime ≤ 51% and Commute time ≤ 20 min and Income = 1]	Rule 6
or [Delay ≥ 4 min and ΔStops ≤ 0 and Commute distance ≤ 8 miles]	Rule 7
or [ΔPleasure ≥ 2 and ΔFamiliarity ≥ 0 and Commute time ≤ 16 min]	Rule 8
Otherwise, continue to use the current route.	Rule 9

Appendix B; Indifference band per individual-situation combination from data-analysis

This appendix contains the detailed values found for the subconscious and conscious indifference bands based on the data-analysis in chapter 3.3.

B.1 Detailed subconscious indifference bands based on perceptions

Table 36 shows the detailed subconscious indifference bands based on the perceptions of individuals as stated in the post-run questionnaire. Only the observations in which an individual i stated that there was no difference in travel time on that OD-pair pq or that one route alternative would be shorter in travel time than the other route alternative, while based on his experienced travel times the other route alternative would be the shorter one, are used. The indifference band is determined as the average experienced travel time difference of that specific individual i on that specific OD-pair pq during the 20 runs t.

Table 36: Detailed subconscious indifference bands based on perceptions***

Individual\OD-pair	OD-1	OD-2	OD-3	OD-4	OD-5	Averages*:
111	-	-	0.75	-	1.98	1.37
112	-	0.60	1.36	-	-	0.98
113	0.06	-	0.36	0.47	-	0.30
114	0.97	-	-	-	-	0.97
115	-	-	-	-	-	-
116	0.61	-	-	-	-	0.61
121	0.63	-	1.75	0.32	-	0.90
122	0.44	0.60	-	-	-	0.52
123	-	-	-	-	-	-
124	-	-	-	-	-	-
125	0.95	-	-	0.18	-	0.56
211	-	-	-	-	-	-
212	0.58	0.36	2.19	0.20	-	0.83
213	-	-	-	-	-	-
214	0.38	0.65	-	-	-	0.52
215	0.39	-	-	0.39	-	0.39
221	0.10	-	0.05	-	0.80	0.32
222	0.38	1.05	1.23	0.48	-	0.78
223	0.08	2.08	1.34	0.57	-	1.02
224	1.16	-	-	-	-	1.16
225	0.00	1.94	-	-	-	0.97
Averages*:	0.48	1.04	1.13	0.37	1.39	0.88**\0.76**

* In calculating the average thresholds, the OD-pair/individual combination in which no incorrect perception was stated are not included.
**Weighted averages.
***Underlined indifference bands are obtained by the statements containing perceptions that the longer route alternative was the shortest, while the non-underlined indifference bands are obtained by the statements containing an indifferent perception.

B.2 Detailed conscious indifference bands based on inertial choices

Table 37 shows the detailed conscious indifference bands based on the inertial choices individuals made during the experiment. For each individual i and OD-pair pq combination the maximum travel time difference of the inertial choices is determined, indicating the magnitude of the indifference band.

Table 37: Detailed conscious indifference bands based on inertial choices

Individual\OD-pair	OD-1	OD-2	OD-3	OD-4	OD-5	Averages*:
111	0.23	-	0.23	0.31	-	0.25
112	0.64	1.35	2.16	-	-	1.38
113	1.13	-	2.10	2.90	-	2.04
114	0.98	0.66	0.09	-	0.78	0.63
115	2.82	1.68	-	-	1.84	2.11
116	0.99	2.32	0.58	0.28	-	1.04
121	0.59	-	2.53	0.74	-	1.29
122	0.44	0.73	2.00	1.13	1.43	1.14
123	-	2.74	0.70	0.74	-	1.39
124	0.85	0.09	1.07	0.03	-	0.51
125	2.41	0.00	0.66	1.30	-	1.09
211	1.12	-	-	0.33	-	0.72
212	2.49	0.03	2.65	2.07	-	1.81
213	0.60	0.79	-	-	-	0.69
214	0.92	0.70	1.53	-	2.04	1.30
215	0.08	-	-	1.99	-	1.03
221	0.59	-	0.42	0.83	-	0.61
222	2.42	0.97	2.27	0.63	2.58	1.78
223	1.18	2.17	3.62	1.33	-	2.08
224	2.78	0.15	-	1.96	0.95	1.46
225	0.30	2.75	-	-	-	1.53
Averages*:	1.18	1.14	1.51	1.11	1.61	1.31**\1.22**

* In calculating the average thresholds, the OD-pair/individual combination in which no inertial choice is made are not included.

** Weighted averages.

Appendix C; Bayesian sampler output analysis

This appendix shows an analysis of the sampler output of the MCMC sampler algorithm within Matlab in order to determine whether the sample can reasonably be treated as a set of random realizations from the target posterior distribution. The analysis methods as suggested by MathWorks (i.e. the computer software company that produced Matlab) are used, see MathWorks (2014).

C.1 Sampler output analysis inertia model

The sampler output for the inertia model is obtained using a burning rate of 350 and a thinning rate of 2000 in order to obtain 1000 samples. This output is found to be a representative sample based on the output analysis using different visualizations of the output and its characteristics.
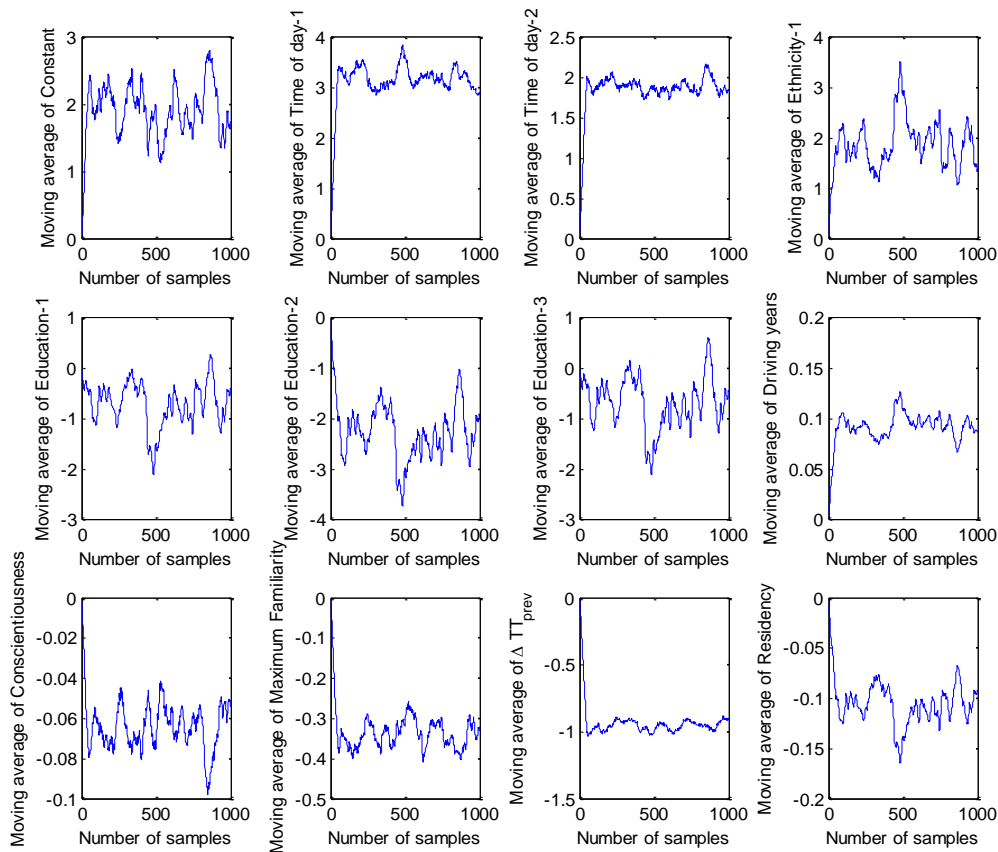

Figure 47: Moving averages of the sampled coefficients for the inertia sub-model (over window of 50 iterations)

Figure 47 shows the moving average plots for the coefficients of the inertia model. These show moving averages over a window of 50 iterations. As a result, the first 50 values are not comparable to the rest of the plot. It is found that for most variables a relatively stationary state is obtained.
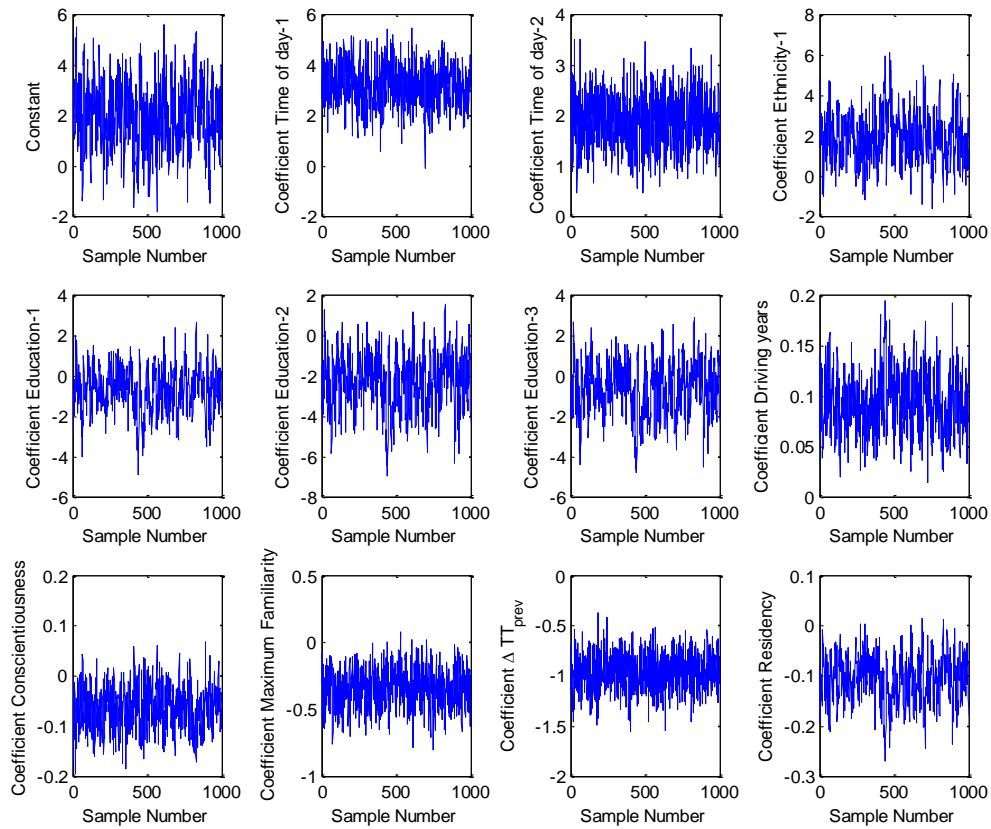
Figure 48: Value of sampled coefficients for the inertia sub-model

Figure 48 shows the sample coefficient values for each variable of the inertia model. It is apparent from these plots that the initial value of the sampling sequence has no influence on the samples, which means that the used burning rate of 350, throwing the first 350 obtained samples away, has done his job. Furthermore, the relatively stationary state is reflected by the horizontal trend that is visible.
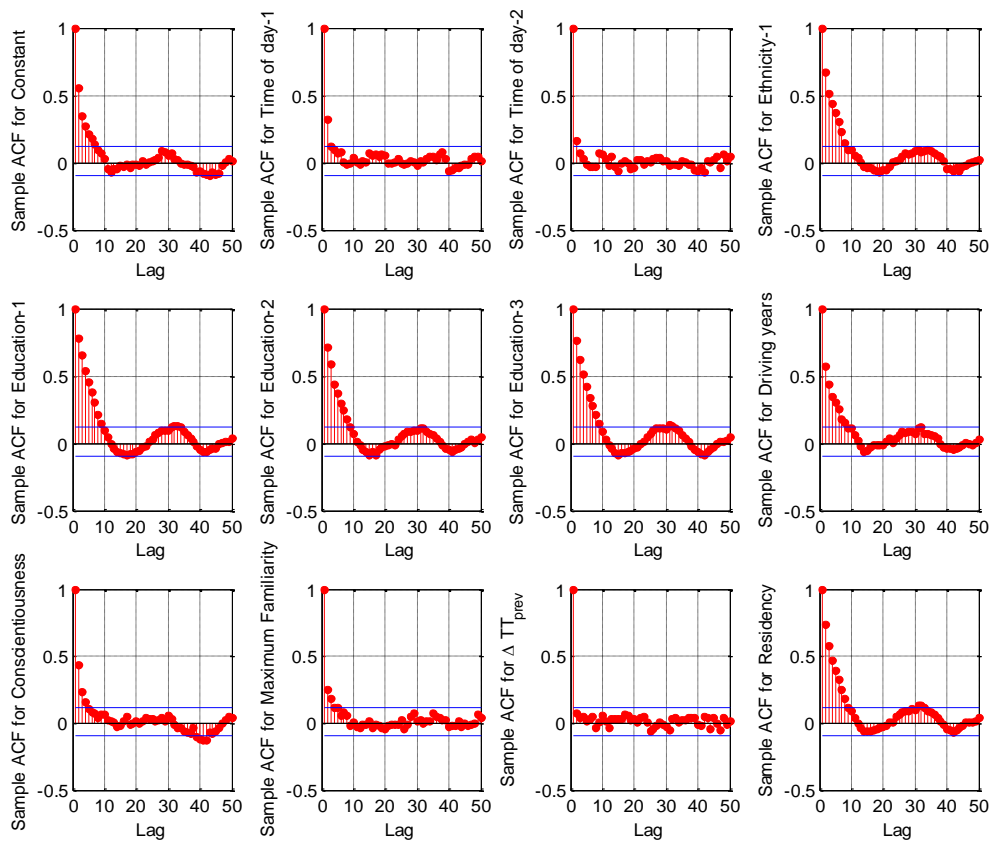
Figure 49: Variations in the autocorrelation of the sampled coefficients for the inertia sub-model

Figure 49 shows the variation in the autocorrelation of the model coefficients of the inertia model. These plots show if the samples mix rapidly and if the sample can be treated as a sample of independent values. A confidence interval of 99% is used, represented by the blue horizontal lines. Within these lines the autocorrelation is not significant. For all variables the samples do mix within the confidence interval, although for some variables this is takes some time, leaving room for improvements. This could be improved by using a higher thinning rate. However, the thinning rate is already set at a very high value of 2000. At this moment, it is believed that this is the best obtained sample in terms of mixing speed as increasing this value did not improve the sample.
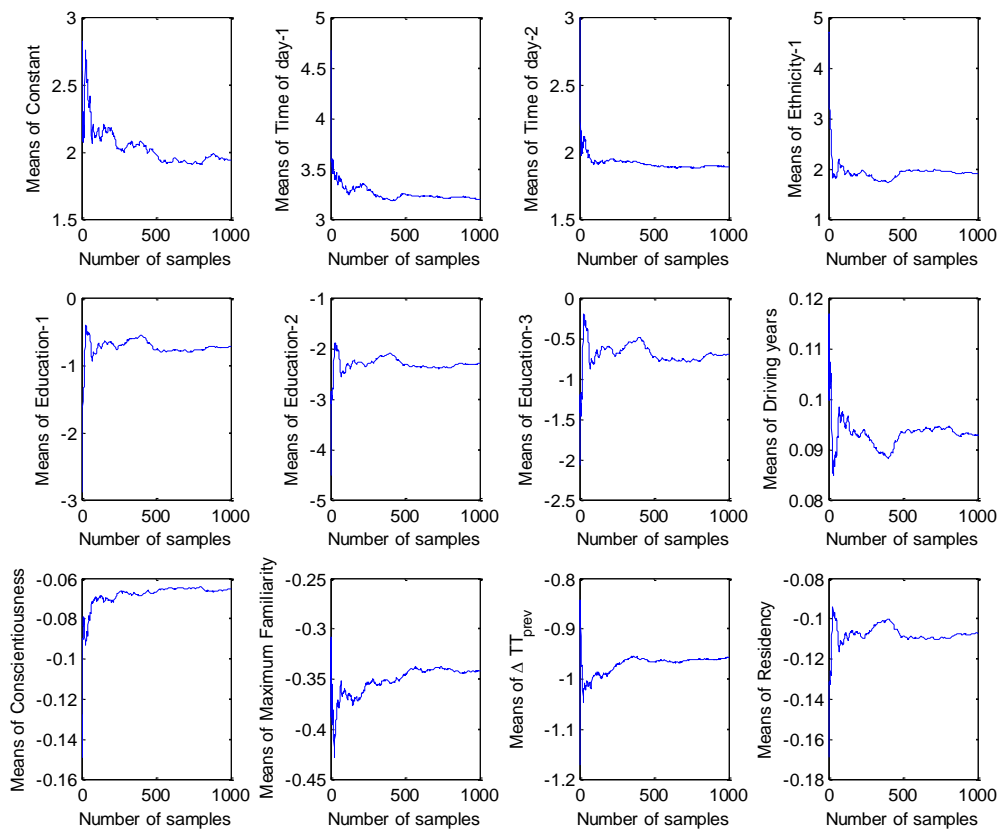
Figure 50: The mean of the sampled coefficients updated after each additional sample for the inertia sub-model

Figure 50 shows the estimated posterior means from the random samples for the inertia model. This indicates if the used sample size is large enough. All means of the coefficients seem to stabilize. Therefore, it is assumed that the used sample size is large enough.

C.2 Sampler output analysis compromising model

The sampler output for the compromising model is obtained using a burning rate of 250 and a thinning rate of 1500 in order to obtain 500 simulated samples. This output is found to be a representative sample based on the output analysis using different visualizations of the output and its characteristics.
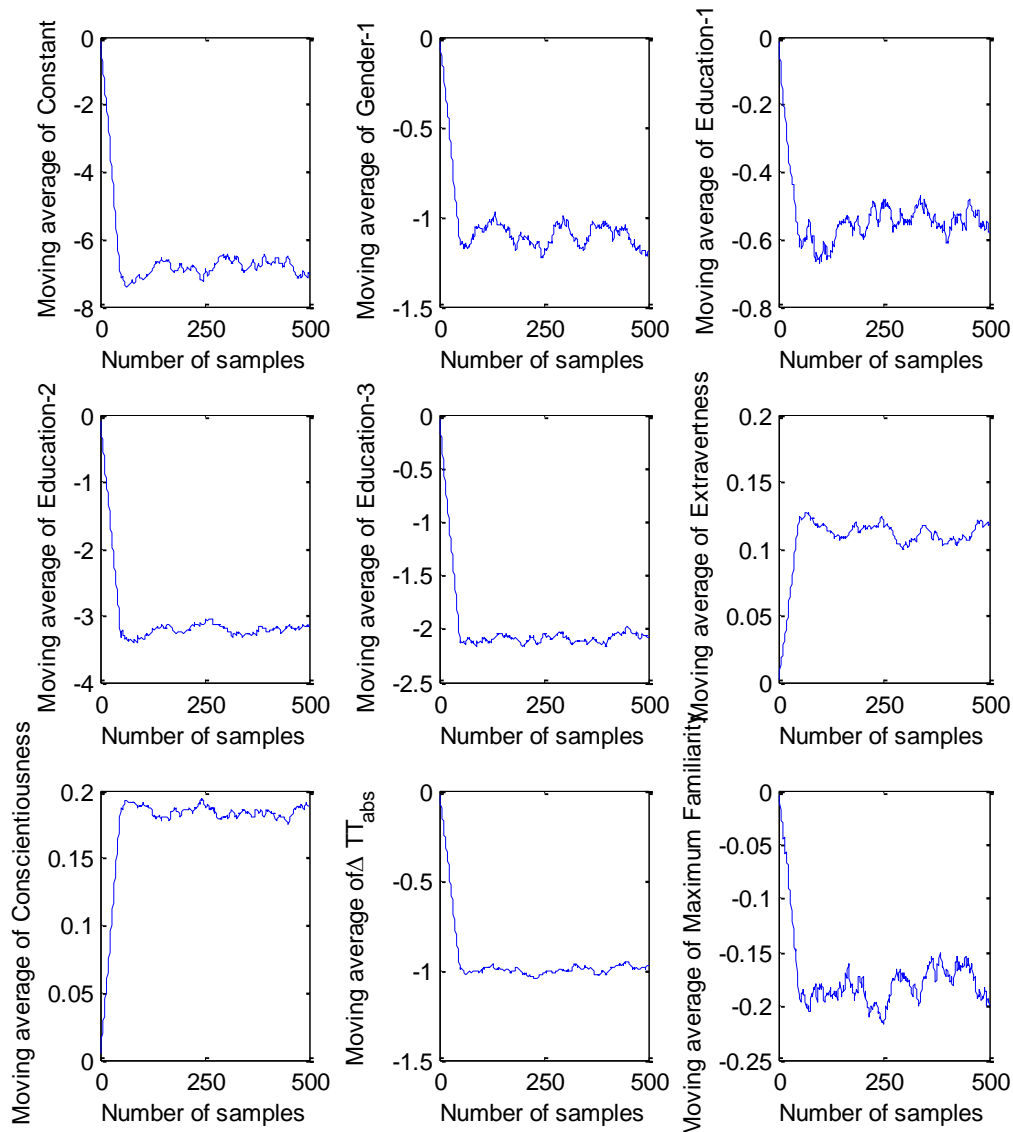

Figure 51: Moving averages of the sampled coefficients for the compromising sub-model (over window of 50 iterations)

Figure 51 shows the moving average plots for the coefficients of the compromising model. These show moving averages over a window of 50 iterations. As a result, the first 50 values are not comparable to the rest of the plot. It is found that for all variables a reasonable stationary state is obtained.
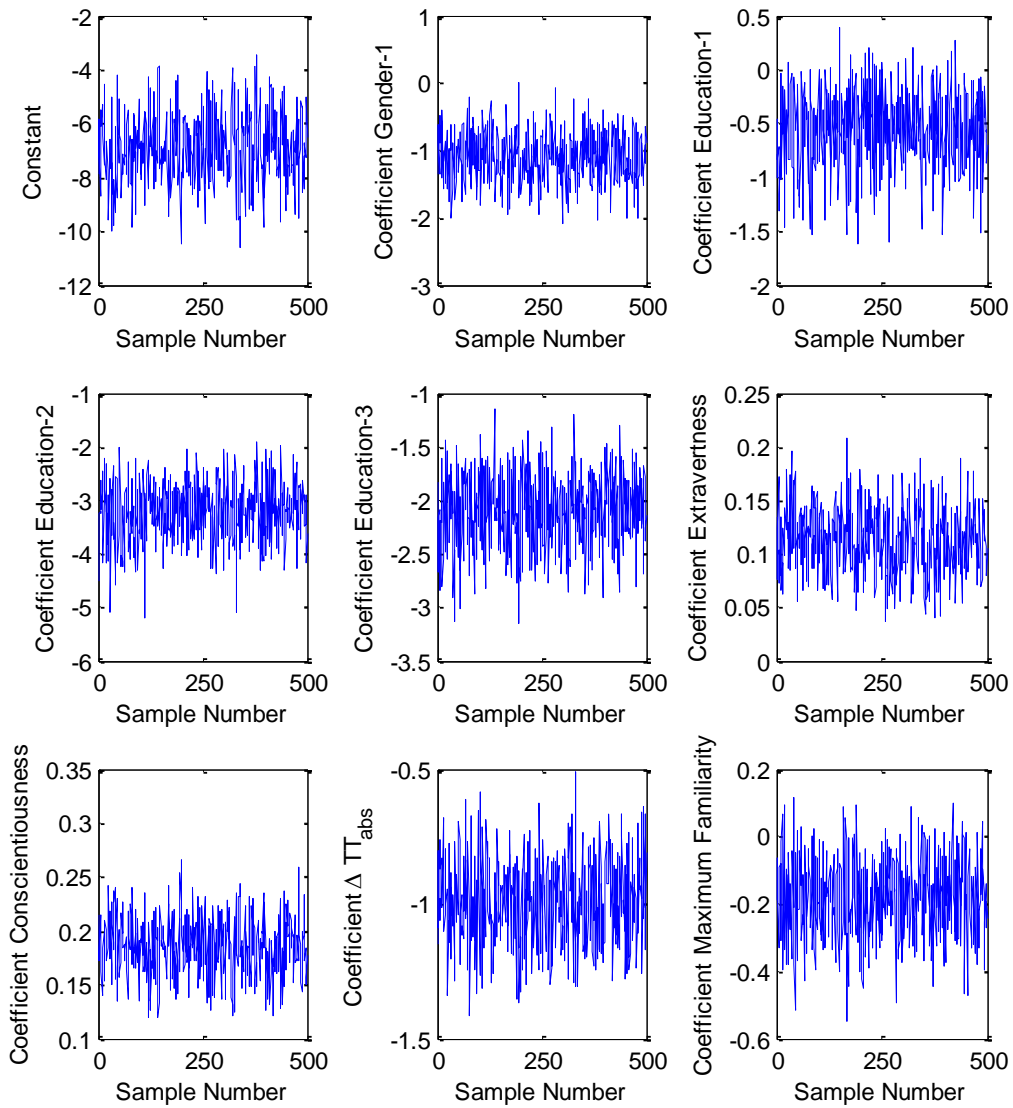
Figure 52: Value of sampled coefficients for the compromising sub-model

Figure 52 shows the sample coefficient values for each variable of the compromising model. It is apparent from these plots that the initial value of the sampling sequence has no influence on the samples for all variables. This means that the used burning rate of 250, throwing the first 250 obtained samples away, has done his job.
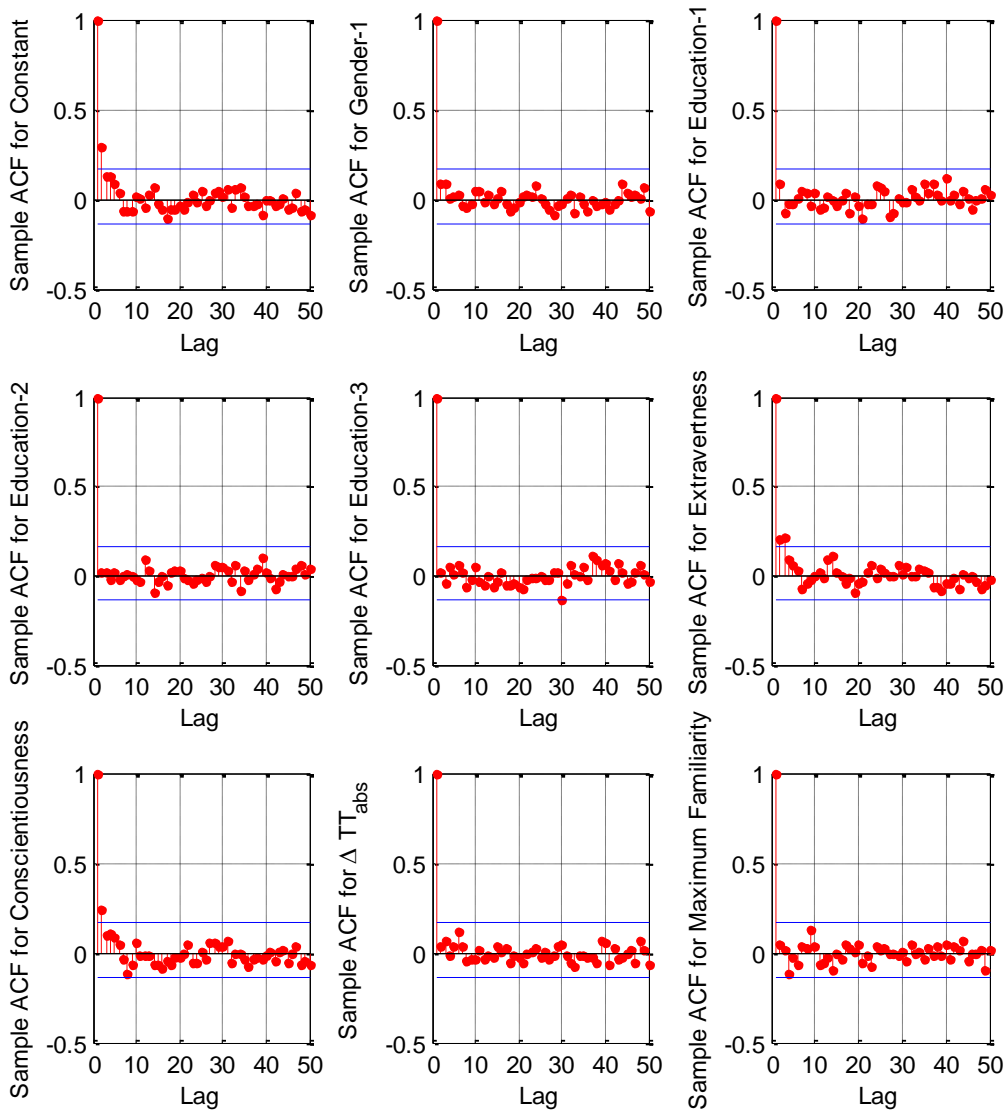
Figure 53: Variations in the autocorrelation of the sampled coefficients for the compromising sub-model

Figure 53 shows the variation in the autocorrelation of the model coefficients of the compromising model. A confidence interval of 99% is used, represented by the blue horizontal lines. Within these lines the autocorrelation is not significant. Based on these plots it can be stated that the samples mix rapidly and can be treated as samples of independent values.
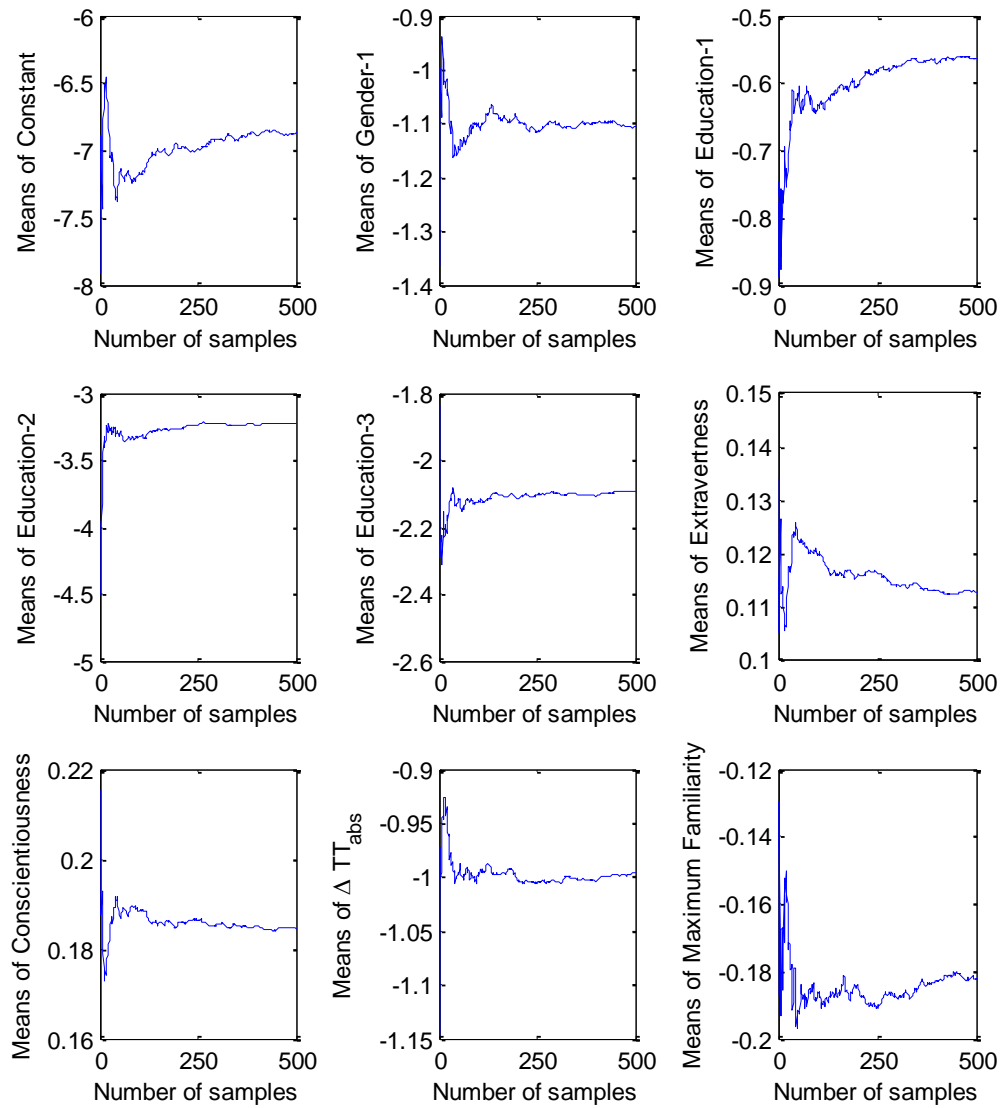
Figure 54: The mean of the sampled coefficients updated after each additional sample for the compromising sub-model

Figure 54 shows the estimated posterior means from the random samples for the compromising model. It is found that all means of the coefficients stabilize reasonably, indicating that the used sample size is large enough.

Appendix D; Indifference band per individual-situation combination from the 2-step-model

This appendix contains the detailed values found for the conscious indifference bands based on the 2-step-model.

13.1.1 Detailed conscious indifference band obtained from 2-step-model

Table 38 shows the detailed conscious indifference bands obtained by the 2-step-model. Using the inertia sub-model the indifference band is found by adjusting the travel time attribute in order to find the probability p of an individual i exposing inertial behavior at OD-pair pq to be 50%, which is assumed to be the switching point. After all, at a probability p lower than 50%, it is more likely that an individual i will make a switching choice, while at a probability p higher than 50% it is more likely that this individual i will stick to his current route choice.

Table 38: Detailed conscious indifference bands based on the 2-step-model

Individual\OD-pair	OD-1	OD-2	OD-3	OD-4	OD-5	Averages*:
111	0	0	0.17	0.17	0.17	0.10
112	-	-	1.25	-	-	1.25
113	3.02	-	3.02	3.02	-	3.02
114	0.24	1.09	0.24	-	0.24	0.45
115	-	-	-	-	-	-
116	2.41	3.52	2.69	2.41	-	2.76
121	0	-	0	0	0	0.00
122	-	10.77	-	-	-	10.77
123	1.81	2.37	2.37	1.81	1.53	1.98
124	-	0	-	-	-	0.00
125	1.06	1.62	1.06	1.06	1.06	1.17
211	2.52	2.42	2.42	2.42	-	2.45
212	0.84	0.84	0.84	0.84	0.84	0.84
213	-	-	-	-	-	-
214	3.17	3.17	3.17	-	3.17	3.17
215	1.13	1.13	1.13	2.25	-	1.41
221	1.11	1.4	-	-	1.4	1.30
222	-	-	-	-	-	-
223	4.39	5.51	-	-	-	4.95
224	1.57	1.85	1.85	-	1.57	1.71
225	0	-	0	0	-	0.00
Averages*:	1.55	2.55	1.44	1.40	1.11	1.67**\2.27**

* In calculating the average thresholds, the OD-pair/individual combination in which no indifference is stated are not included.
** Weighted averages.