The Impact of Traffic Information:
Dynamics in Route and Departure Time Choice
Publication of this thesis was sponsored by:

ANWB, The Hague
BMW AG, Munich, Germany
BUREAU GOUDAPEL COFFENG, Deventer
CROW, Ede
DRIVE COMMISSION OF THE EUROPEAN COMMUNITIES, Brussels, Belgium
KOLPRON CONSULTANTS, Rotterdam
KONINKLIJK NEDERLANDS Vervoer, The Hague
KORPS LANDELIJKE POLITIEDIENSTEN, Driebergen
LUCHTHAVEN SCHIPHOL, Schiphol
PEEK TRAFFIC, Hilversum
PSA PEUGEOT CITROEN, Paris, France
RADIO HOLLAND GROUP, Amsterdam
RAI, Amsterdam
RIJKSWATERSTAAT DIRECTIE GELDERLAND, Arnhem
SEMA GROUP BENELUX, Brussels, Belgium
STICHTING WEG, MOBILITEIT & INFRASTRUCTUUR, The Hague
STORK NOLTE INFRA TECHNIEK, Eindhoven
TELE ATLAS NEDERLAND, Den Bosch
TRANSPORT RESEARCH LABORATORY, Crowthorne, Great Britain

CIP-GEGEVEN KONINKLIJKE BIBLIOTHEEK, DEN HAAG

Mede, Peter Hendrikus Johan van der

The impact of traffic information: dynamics in route and departure time choice / Peter Hendrikus Johan van der Mede, Eric Cor van Berkum. - [S.l.: s.n.].-lll.
Proefschrift Technische Universiteit Delft. - Met lit.
opg. - Met samenvatting in het Nederlands.
ISBN 90-9006318-8
NUGI 849
Trefw.: verkeersinformatie / routekeuze ; modellen.

Cover design: Mart. Warmerdam, Halfweg
Cover photo: Copyright 1976 by Newsweek, Inc. Newsweek, Lester Sloan
Printed by: Universiteitsdrukkerij Delft
Stellingen van Peter H.J. van der Mede
behorende bij het proefschrift
The Impact of Traffic Information:
Dynamics in Route and Departure Time Choice

1. De in de verkeerskunde gangbare aannemer dat automobilisten in grote mate alwetende en optimale beslissers zijn is onjuist. In werkelijkheid zijn zij niet goed op de hoogte van alle weerstanden in een netwerk en wegen zij beschikbare alternatieven niet vaak tegen elkaar af.

2. Bij herhaalde beslissingen spelen gewoonten als beslisregel een veel grotere rol dan nutsmaximalisatie.

3. Vier belangrijke gevolgen van het aanbieden van informatie over de toestand van het wegennet aan automobilisten zijn dat automobilisten:
   (a) kennis nemen van eerder niet waargenomen alternatieven;
   (b) waargenomen alternatieven meer tegen elkaar gaan afwegen;
   (c) keuzen minder op gewoonte baseren;
   (d) bij het afwegen van alternatieven meer belang gaan hechten aan de aangeboden informatie-elementen.

4. Als beslissers een grote mate van onzekerheid ervaren is de betrouwbaarheid van geboden informatie van ondergeschikt belang: zij zullen de informatie steeds blijven gebruiken.

5. Met het op steeds grotere schaal beschikbaar komen van informatie zal in analogie met het mobiliteitsprobleem in de komende decennia het communicatieprobleem steeds groter worden.

6. Een groot nadeel van modellen van menselijk gedrag is dat wat ermee beschreven wordt vaak als het gedrag zelf wordt beschouwd.

7. Het onderscheid tussen technische en sociale verkeerskunde is niet functioneel. Om het wetenschappelijk gehalte van de verkeerskunde te vergroten dient deze zo snel mogelijk een brede interfacultaire studierichting te worden.

9. Popper's principe van falsificeerbaarheid (Popper, 1963) heeft de theorievorming in de gedragswetenschappen beperkt en heeft in de gedragswetenschappen niet geleid tot de beoogde groei van wetenschappelijke kennis.

10. De dwang tot publiceren in de psychologie leidt niet tot meer wetenschappelijke kennis en verkleint bovendien de kans dat van belangwekkende artikelen kennis genomen wordt. De zegswijze 'publish or perish' zou derhalve vervangen moeten worden door 'publish and perish'.

11. De vaststelling dat resultaten van sociaal wetenschappelijk onderzoek vaak voor de hand (lijken te) liggen, duidt niet op trivialiteit maar op plausibiliteit.

12. Uitbreiding van het traditionele openbaar vervoer is geen oplossing voor het automobiliteitsprobleem. Van efficiëntieverbetering door nieuwe informatietechnologie mag in de komende jaren meer verwacht worden.

13. De unificatie van de natuurwetenschap is waarschijnlijker dan die van de gedragswetenschap.


Referenties:
Stellingen van Eric C. van Berkum
behorende bij het proefschrift
The Impact of Traffic Information:
Dynamics in Route and Departure Time Choice

1. Evenwicht in een verkeerssysteem ontstaat als gevolg van gewoontevorming en niet als gevolg van convergerende reistijden.

2. De definitie van een stochastische statische toedeling kent dezelfde inconsistentie als de definitie van een 'bounded rational' statische toedeling. De onderliggende aannames bij zowel het stochastische element als bij het 'bounded rational' element veronderstellen dynamiek (zie hoofdstuk 3).

3. Inertie in gedrag moet niet worden verward met gewoontevorming. Gewijzigde omstandigheden die in geval van inertie een vertraagd effect hebben, kunnen in geval van gewoonte ook geen effect hebben.

4. Traditionele routekeuzemodellen zijn onvoldoende in staat het werkelijke gedrag te simuleren. Onwetendheid, onzekerheid en onachtzaamheid worden er niet of nauwelijks mee beschreven.

5. De veronderstelling van Wardrop dat in een evenwichtssituatie alle gebruikte routes even lang en alle niet gebruikte routes langer zijn, is niet realistisch. Naarmate automobilisten beter geïnformeerd zijn, wordt deze veronderstelling realistischer.

6. Het verstrekken van onjuiste informatie heeft minder dramatische gevolgen voor de gepercipieerde betrouwbaarheid van het informatiesysteem dan vaak wordt gevreesd.

7. Er zijn gevallen waar de (on)juistheid van informatie niet door de ontvanger kan worden waargenomen. Dit biedt mogelijkheden om informatie te gebruiken als verkeersmanagementmaatregel die erop gericht is de verkeersstroom richting systeem-optimum te bewegen.
8. Door informatie te verstreken aan verkeersdeelnemers worden betere beslissingen genomen, zelfs wanneer de verkeersdeelnemers al zeer goed op de hoogte zijn met de verkeerssituatie. Betere beslissingen impliceren minder files en kortere reistijden.

9. Het opnemen van verschillende disciplines in de opleiding tot verkeerskundige zal de invoering van informatica in het verkeer vergemakkelijken.

10. 'Value of time' is een ongeschikt hulpmiddel om filekosten te berekenen.

11. De rol die wetenschappers en kunstenaars vroeger in bewustwordingsprocessen hadden schijnt tegenwoordig te zijn overgenomen door beroemdheden uit de wereld van het amusement.

12. Introductie van informatiesystemen in het verkeer is een stimulans voor de economie. Zo kan een tijdige omschakeling in de defensie-industrie naar de ontwikkeling van deze systemen deze industrietak redden van massaoftslagen.

13. De niet-nationalistische geest van Nederlanders heeft tot gevolg dat de rol van Nederland in de EG marginaal zal blijven.

14. Elke groepering die de universele rechten van de mens niet onderschrijft, heeft geen politiek bestaansrecht.

15. De bewering dat oorlog goed is voor de economie getuigt van het niet respecteren van het menselijk leven, en bovendien van het niet durven nemen van werkelijke beslissingen om de economie te stimuleren.

16. Psychologen zijn nog eigenwijzer dan wiskundigen.
The Impact of Traffic Information: Dynamics in Route and Departure Time Choice

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Technische Universiteit te Delft
op gezag van de Rector Magnificus
prof. ir K.F. Wakker
in het openbaar te verdedigen in
de aula der universiteit
op 9 november 1993 des namiddags 14.00 uur

te 14.00 uur door
PETER HENDRIKUS JOHAN VAN DER MEDE
geboren te Rotterdam
doctorandus in de psychologie
Verantwoordelijk voor de
hoofdstukken 2, 4, 6 (deel I) en 8
en bijlage D

te 15.15 uur door
ERIC COR VAN BERKUM
geboren te Hengelo (O)
wiskundig ingenieur
Verantwoordelijk voor de
hoofdstukken 3, 6 (deel II) en 7
en de bijlagen A, B en C

Gezamenlijke verantwoordelijkheid
wordt gedragen voor de
hoofdstukken 1, 5 en 9
Dit proefschrift is goedgekeurd door de promotoren:

Prof. dr A.R. Hale en Prof. dr ir R. Hamerslag
What's that?
What?
That, what you got in your hand.
A picture.
A picture of what?
A picture of ... a picture of Paris.
Paris? Really?
Yes. A picture of a piece of Paris.
Where'd you get a picture of Paris? Can I see it?
Yes.
This is it? This is Paris? Looks just like Texas to me.
It is.
Paris, Texas?
It's right here on the map.

Sam Shepard, Paris, Texas
Acknowledgements

Doctoral dissertations are seldom the sole work of the authors. Several persons and institutions have contributed to this dissertation, and without them the tasks we had set out, would certainly have been much harder, if not impossible, to fulfill. First of all we want to thank Rudi Hamerslag and Andrew Hale, our promotors. Rudi Hamerslag immediately saw the relevance of our work and encouraged us both to write this thesis. He has been a stimulating force throughout the project. We want to thank Andrew Hale in particular for his critical comments, that both guided and inspired us, and without doubt improved the quality of our work.

As far as the original idea for the model is concerned, we are indebted to EC DRIVE Central Office and our co-members of the EUROTOPP Consortium, since they created a context in which the outset of this work took shape. Particularly we would like to thank Phil Goodwin of TSU Oxford for his enthusiasm, and Kay Axhausen of Imperial College London, who convinced us of the usefulness of an individual approach.

Our work would not have been possible if we had to collect the data which were used ourselves. We would like to thank Wiel Janssen from the Institute for Perception (IZF TNO) who provided us with the dataset from a study he carried out with two of his colleagues. We also thank the participants in the experiments we carried out ourselves.

We were privileged to be allowed to use data from Rijkswaterstaat Noord-Holland on route choice behaviour. These data were collected by our colleagues Bolie Rühl and his crew. Last but not least, we are grateful to Willemjjan Schouten of Rijkswaterstaat Noord-Holland for his support to Chapter 7.
Contents

Acknowledgements v

Preface 1

Symbols 3

1 Background and Research Approach 7
   1.1 Introduction 7
   1.2 Object of the Study 10
   1.3 Assumptions and Limitations 11
   1.4 Outline of the Thesis 16

2 Motorist Information Systems 19
   2.1 Introduction 19
   2.2 Motorist Information 20
   2.3 Motorist Information Systems 25

3 Review of Existing Modelling Approaches 31
   3.1 Introduction 31
   3.2 Static versus Dynamic Approaches 33
   3.3 Equilibrium versus Non-Equilibrium Approaches 35
   3.4 Deterministic versus Stochastic Approaches 35
   3.5 Static Approaches 36
   3.6 Within-day Dynamic Approaches 38
   3.7 Day-to-Day Dynamic Approaches 43
   3.8 A Micro-Simulation Approach 47
   3.9 Effects of Information: Capabilities of Different Approaches 49
3.10 Effects of information: Static Approaches 49
3.11 Effects of Information: Deterministic Approaches 50
3.12 Effects of Information: Within-day Dynamic Approaches 51
3.13 Effects of Information: Day-to-Day Dynamic Approaches 52
3.14 Discussion 53

4 Dynamic Decision Making in Travel Behaviour 57
4.1 Introduction 57
4.2 Decisions and Dynamics 59
4.3 Knowledge, Experience and Learning 62
4.4 Information and Uncertainty 64
4.5 Knowledge Attributes 65
4.6 Decision Rules 66
4.7 Variability and Habit 68

5 Towards a Model Specification 73
5.1 Introduction 73
5.2 Assumptions and Foundations 73
5.3 Summary of Goals, Foundations and Behavioural Assumptions 78

6 Model Specification 81
6.1 Introduction to the Chapter 81
6.2 Part I: Outline of the Model 81
6.3 Generation of Knowledge on Structure 85
6.4 Initial Values 87
6.5 Perceived Utility Maximization 87
6.6 Habitual Choice and Updating Habit 88
6.7 Updating Expectations 89
6.8 Departure Time Choice and Route Choice 89
6.9 Credibility of Information and Compliance 90
6.10 Part II: Introduction 92
6.11 The Individual 92
6.12 Knowledge on Structure 92
6.13 Expectations 95
6.14 Route Choice Without Exogenous Information 96
6.15 The Relation between the Information System and the Individual 101
6.16 Descriptive Information 101
6.17 Prescriptive Information 104
6.18 Credibility of Information 105
6.19 Departure Time Choice 107
6.20 Loading 110
7 Tests and Validation: Descriptive Information 113
  7.1 Introduction 113
  7.2 The RIA Variable Message Sign 114
  7.3 The Panel Study 115
  7.4 Model Specification 117
  7.5 Initial Values 121
  7.6 Estimation Procedure 123
  7.7 Results 124
  7.8 Discussion 132

8 Tests and Validation: Prescriptive Information 135
  8.1 Introduction 135
  8.2 Method 136
  8.3 Results 141
  8.4 Discussion 145

9 Conclusions and Implications 149
  9.1 Introduction 149
  9.2 Research Goals 149
  9.3 Conclusions 150
  9.4 Model Specification: Remaining Questions 162
  9.5 Recommendations for Future Research 164

References 167

Mathematical Preliminaries 177

Appendices 181
  A Maximum Likelihood Estimation 181
  B Algorithms for Static Deterministic and Stochastic User
    Equilibrium 185
  C Effectiveness of Information Systems in Networks With and Without
    Congestion (189)
  D Sensitivity Tests 199

Samenvatting (summary in Dutch) 211

Curricula Vitae 217
The work that is presented in this thesis resulted from a close collaboration that originated in 1989 when our firm got involved in the DRIVE I EUROTOPP project of the European Community (e.g. Axhausen et al., 1991).

The EUROTOPP project aimed "to provide transport planners with a tool which is suitable for general transport planning practice, including the impact of both road transport informatics and other transport policies". The project was completed at the beginning of 1992 (EUROTOPP, 1992) and was carried out by a consortium of eight institutions in five member states of the European Community.

The proposed framework for the EUROTOPP model was a dynamic, activity-oriented and information-sensitive microscopic simulation tool. Within this framework the model uses a sample of simulated households to model the evolution of travel behaviour in daily, medium-term and longer term time frames.

Our main responsibility in the EUROTOPP project was (a) the development of a specific module of the model which deals with travel-choice behaviour at the daily level and (b) the conceptualization of the influence of different information scenarios (Van Berkum & Van Der Mede, 1990). As it goes, during this work new ideas emerged which could not be fitted into the model.

---

1 Transport Studies Unit, University of Oxford, United Kingdom
Bureau Goudappel Coffeng, the Netherlands
CETE Méditerranée, France
INOVAPLAN, Germany
Institut für Verkehrswesen, Universität Karlsruhe, Germany
ITS, Universiteit Nijmegen, the Netherlands
Robotiker, Spain
Syseca Temps Reel, France
specifications as proposed originally to DRIVE Central Office. This was not only due to time and budget restrictions, but also to the fact that the software development for the model was carried out by other specialized partners, and definite model specifications were required in a rather early stage of the project. So, next to the work carried out within the EUROTOPP consortium, we further developed our ideas in a model called BEAST (Behavioural Approach to Simulating Travellers; Van Berkum and Van der Mede, 1990; Van Der Mede & Van Berkum, 1991). This model deals with route, mode and departure time choice and information. In this context also a validation study of the route choice process and consequences of a variable message sign was carried out. For that study data were obtained from laboratory experiments (Van Der Mede & Van Berkum, 1992).

The EUROTOPP project was highly ambitious and the final result of the project has not been altogether satisfactory. Particularly the chosen activity-based approach caused severe problems. These problems were encountered during the development of the proposed model and could not be solved during the time allowed. Unfortunately, the EUROTOPP project was not continued in the DRIVE II program.

Though far more limited in scope than the complete EUROTOPP project, the work that was carried out by us seemed to have enough merit to continue. The fact that a research project that we carried out for Rijkswaterstaat Noord-Holland (BGC, 1992a, 1992b, 1993) could provide the necessary data for a first validation study of the model with real-life dynamic data, added to this decision. We decided to write a thesis in which the model is presented comprehensively.

In our view our collaboration has been very fruitful. We feel that our different backgrounds, applied mathematics and psychology, facilitated the exchange of ideas, methods and solutions from both disciplines. It is clear that we as authors accept full responsibility for this thesis as a whole.
Symbols

General

All variable bold denote vectors. Vector dimension is understood from its context.
Subscripts or superscripts that are generally used are:
i individual
k arrival time interval
l link
r route
t day or period
w wave

List of Variables

$at_{it}$ mean of an arrival time interval
$b_{it}$ number of bad experiences with info-system
$B_{it}$ buffer for compliance
$c_{it}$ credibility of info-system
$d_{it}$ departure time
d destination
$D_{it}$ directed graph representing a network
$DT_{it}$ planned departure time
$ef_{irt}$ experienced queue length
$ek_{irt}$ experienced travel cost
$ett_{irt}$ experienced travel time
$E_{it}$ expectations set
$f_{irt}$ expected queue length
$ff_{ipt}$ ratio between travel time according to info system and expected travel time
$g_{it}$ number of good experiences with info-system
\(H_i\)  habit strength for route choice
\(H_{\max}\)  maximum habit strength for route choice
\(HH_{it}\)  habit strength for departure time choice
\(HH_{\max}\)  maximum habit strength for departure time choice
\(l_i\)  information itself
\(IS_i\)  structure of the information
\(k_{itr}\)  expected travel cost
\(KS_{it}\)  knowledge on structure (known network)
\(L\)  linkset
\(L(c)\)  value of log likelihood function when only an alternative specific constant is included
\(L(0)\)  value of log likelihood function when all parameters are zero
\(L(x^*)\)  value of log likelihood function at its maximum
\(N(0,1)\)  normal distribution with mean 0 and variance 1
\(N\)  nodeset
\(o\)  origin
\(P_{itr}\)  probability that an individual chooses a route at a certain day
\(pat_{it}\)  preferred arrival time
\(PC_{itr}\)  probability that an individual complies with the advise
\(PIN_{itr}\)  probability that a route is chosen out of habit
\(PT_{it}\)  planned trip
\(PUM_{itr}\)  probability that a route is chosen out of utility maximization
\(p\)  path
\(P\)  pathset
\(P_{itr}\)  probability that a route is chosen by an individual on a day
\(PP_{itd}\)  probability that a departure time is chosen by an individual on a day
\(Pr\)  probability
\(nt\)  number of arrival time intervals
\(R_{it}\)  planned route
\(ria_{itr}\)  queue length information according to the RIA sign
\(std_{itr}\)  standard deviation in travel time
\(std_{itr}^2\)  variance in travel time
\(sk_{itr}\)  standard deviation in travel cost
\(sk_{itr}^2\)  variance in travel cost
\(tt_{itr}\)  expected travel time
\(T\)  origin-destination trip matrix
\(TT_{ipt}\)  travel time according to a descriptive info-system
\(U(0,1)\)  uniform distribution between 0 and 1
\(U_{itr}\)  perceived utility
\(v\)  speed
\(V_{itr}\)  expected utility of a route
\(V_{itr}^k\)  expected utility of a route for an arrival time interval
\(w\)  wave
Symbols

$W_{tkr}$ expected utility of an arrival time interval given a route
$q$ flow

Greek Symbols

$\alpha$ parameter for speed with which habit builds up
$\beta_k$ parameter in the utility function for the $k^{th}$ attribute
$\delta_{xyz}$ is 1 or 0, dependent on conditions
$\epsilon_{itr}$ error term
$\zeta(\rho)$ speed on a link as function of the density
$\lambda(p)$ network induced by a path
$\Lambda(D_{it})$ routeset in a network
$\tilde{\Lambda}(D_{it})$ set of routes, ordered by travel time
$\tilde{\Lambda}_M(D_{it})$ first $M$ elements of the ordered set of routes
$\lambda_l$ physical length of a link
$\rho_l$ density on a link
$\sigma_{it}$ is 1 when trip was satisfactory and 0 otherwise
$\zeta_{it\tau}$ state of a trip
$\tau_\tau(\rho)$ travel time on a link as function of the density
$\Phi$ function that determines first element in an ordered set
$\psi$ learn parameter for routes
$\Psi$ learn parameter for departure times
$\omega_j$ bounded rationality bounds, for $j=1,2,3$
$\omega_{DT}$ ordering of a set with key $DT$

Mathematical Symbols

$\lceil x \rceil$ maximum natural number less or equal to $x$
$\lfloor x \rfloor$ minimum natural number greater or equal to $x$
$\forall$ for all
$\exists$ there is
Background and Research Approach

1.1 Introduction

Both transport authorities and individual drivers aim for 'optimal' transport. Several studies have shown that driver behaviour is 'suboptimal'. Even if we accept the fact that people will use cars for their transportation, suboptimal driving due to erroneous route choice and timing of travel will cause more congestion and pollution than necessary. Suboptimality or inefficiency is usually operationalized as excess distance or excess travel time. Excess distance means excess over the shortest possible route and excess travel time means excess travel time over the shortest (quickest) route under prevailing circumstances. The extent of inefficient use of the highway system was investigated by King (1986) and King & Mast (1987). In these studies destination-free "pleasure" driving was excluded from the analysis, and the concept of excess travel rested on two assumptions. First, that vehicle trips represent an attempt to go from one point on the highway system to another. Second, if given perfect information, drivers will select the route that minimizes travel time (or costs) in traversing the network. They reported that driver "navigational waste", or excess travel, is about 6 percent of all distance and 12 percent of all time spent in travel by non-commercial motorists. Jeffery (1986) reported a study on the same subject and found excess travel distance of about six percent in England. Reasons for inefficient driving may be that drivers are not well informed about available alternatives or about the current state of the road network. In that case, provision of improved information might induce more efficient driving.

If driver information-systems could reduce excess travel, they could also provide a contribution to the alleviation of congestion and the burden that is put on the environment by traffic. However, a reduction of excess travel time will not necessarily lead to a reduction of excess travel distance. In congested networks
routes which are longer in distance may be shorter in travel time. The
environmental impact of this is as yet unknown.

At this time a large number of information systems have been developed.
The wide range of applications of advanced transportation technology concerning
navigation, communications, identification and control are generally known
as intelligent vehicle-highway systems, or IVHS\(^1\) (TRB, 1991\(^a\), 1991\(^b\)). IVHS
utilizes computer and communications technology. Some systems provide
information to travellers about road and transit travel conditions, and enable
them to make more informed choices about routes, times, and modes of travel.
Other systems are intended to assist drivers and reduce accidents through
automation of vehicle control. Still others are designed to monitor, guide or
control the operation of vehicles and allow authorities to manage transportation
systems and control traffic more efficiently.

In the field of transport, it is widely believed that IVHS technology has the
potential to create a fundamental change in the surface transportation system
(Rijkswaterstaat, 1992; TRB, 1991\(^b\)). Major IVHS applications are expected
to contribute to the alleviation of congestion and environmental pollution caused
by traffic and to benefit traffic safety. Furthermore, IVHS can allow improved
provision of public services, enable a broad range of transportation options
to be more easily implemented and create market opportunities for the private
sector. Whether all these expectations will be fulfilled eventually remains to
be seen.

Both the private and public sector have recognized the importance of IVHS.
In recent years programs were, and still are maintained for research, testing
and initial implementation of IVHS. In Europe, the European Community initiated
the PROMETHEUS (PROgraM for European Traffic with Highest Efficiency
and Unprecedented Safety) and DRIVE programs (Dedicated Road Infrastructure
for VEHICLE safety). Where PROMETHEUS emphasizes on-board vehicle systems,
DRIVE takes a more transportation systems oriented approach. As outcome
functions and standards for a so-called Integrated Road Transport Environment
(IRTE) will be defined. In the United States the IVHS-America organization
was put forward, with largely the same objectives as the European initiatives.
Principal objectives of these initiatives are to introduce information systems
into transport in order to reduce the environmental impact of traffic and to
increase safety. Contrary to the European and North-American point of view,
the development of IVHS systems in Japan has been predominantly treated
as an application of existing technology and not as the development of a wholly
new technology.

\(^1\) IVHS is the term used in the US. In Europe IVHS is also known as RTI, Road Transport
Informatics or as ATT, Advanced Transport Telematics. Throughout this thesis the term IVHS
will be used.
It is not claimed that IVHS technology will be the sole solution to solve existing and future problems in transport (Goodwin, 1991; TRB, 1991). Established tools like new construction and existing traffic management methods will not be superseded. However, new technology could allow other tools to function more effectively.

One of the questions that have been raised, is to what extent IVHS technology can contribute to the alleviation of congestion and environmental pollution? Though many studies have been carried out to answer this question (e.g. Allen et al., 1991; Bonsall, 1992; Bonsall & Parry, 1991; Hamerslag & Van Berkum, 1991; Iida, Aikyama & Uchida, 1992; Koutsopoulos & Lotan, 1989; Stevens & Hounsell, 1992), no definite answer has been given yet. One of the main reasons for this is that a comprehensive methodology to deal with relevant travel behaviours in information environments has not yet been developed. Most tools to study the transport system that were developed in the pre IVHS period are not suited to deal with the question in what way drivers respond to information. The development of a methodology which is suited to deal with this question is one of the main goals of this thesis.

IVHS technology connects the three main components of the transport system: the infrastructure, the vehicle and the traveller (Figure 1.1). IVHS can collect data from the infrastructure, e.g. the roadway network, from single vehicles and/or travellers, and from these data can generate traffic information and transmit this information to users or vehicles. Any methodology that aims to deal with the impact of IVHS must deal with these three components and their interrelations.

![Diagram of IVHS triad](image)

**Figure 1.1** The triad of IVHS

IVHS include a large number of different systems. Because of their diversity and complexity it would neither be wise nor possible to attempt to address all these systems in this thesis. We have therefore decided to focus the work for this thesis on a number of systems that have been and are being developed for car drivers. These systems aim to make the drivers task easier, by letting them make better decisions. In particular those information systems that provide
drivers with information relevant to route choice and timing decisions will be the subject of this thesis.

The primary aim of such information systems is to help drivers make more informed and, as a result, optimal travel decisions. In this case, the word optimal is not unequivocal. Optimal can be understood at the individual user level: the driver may have individual benefits, because the information makes it possible to avoid congestion, or reduces the attention necessary to carry out the route following task. Optimal can also be understood at the system level: more informed decisions of motorists may lead to a more efficient utilization of the transport system. Therefore, not only drivers but also transport authorities will be interested in the benefits of these systems.

It has been shown that user and system optima need not be identical (Braess, 1968). Since strategies underlying information provision to motorists are either based on user or system optimization, the question arises which strategy is most efficient to both users and transport authorities. To answer this question a methodology is necessary which is suited to deal with travel behaviour under both strategies of information provision. This thesis aims to develop such a methodology, but does not attempt to answer the basic question.

Obviously, the expected individual benefits for car drivers may indicate that a commercial market for these systems exists. Considering the number of car drivers this market is potentially very large.

1.2 Object of the Study

The main research goal of this thesis is to develop and validate a methodology to predict or estimate the influence of different, new information systems for car drivers. To do this, either an aggregate or non-aggregate approach can be followed. An aggregate approach describes the flows within the traffic system, while a non-aggregate approach describes the behaviour of the individuals that make up the traffic system. The major advantage of aggregate approaches is their computational convenience. However, as will be shown in Chapter 3, it is not possible to use such an approach for our present purpose. For now, it suffices to state that, since traffic flows are generated by individual travellers, the proposed methodology must be specific about the influence of information systems on individual travel behaviour.

Further, for such a model the link between individual travel behaviour and traffic flows must be established by an appropriate loading technique, that is, an algorithm which assigns individual drivers (cars) to the transport network in time. However, it is not necessary to establish this link before the general methodology on the individual behavioural level has been developed adequately.

Concerning the main goal of this thesis, two questions may be raised. Firstly, why is it important to predict effects of new information systems in transport,
and secondly, why is it important to develop such a methodology? Prediction of the effects of new driver information systems is primarily important because prediction can serve as a decision support tool to policy makers and traffic authorities. The relevance of such a tool lies in the fact that in many cases the introduction of an information system in transport involves large public and commercial investments. To decide what information system will be most beneficial in a given situation compared to the implementation costs, it is important to estimate the effects of proposed information systems already before their introduction. For policy makers and traffic authorities it will be relevant to know what effects can be expected, and what the order of magnitude of these effects could be. Both may want to have such estimates for different information strategies, in order to make the right decision on what information strategy and what system under the prevailing circumstances will be most appropriate.

The primary reason to develop such a methodology lies in the fact that existing tools to estimate the influence of various traffic measures are insufficiently suited to deal with information systems as an input variable. These tools or methodologies either assume that all travellers are already perfectly informed, or, when not, these methodologies can only cope with information as some abstract quality, or can evaluate only one specific, and not necessarily realistic information system. These point will be addressed more thoroughly in Chapter 3. Partly, these shortcomings are is due to the fact that the behavioural assumptions underlying the current methodologies are insufficient to address questions on how travel behaviour may be influenced by different information systems. More specifically, the behavioural decision processes in travel and the role of information in these processes are inadequately specified in the current tools. The current research therefore also attempts to formulate a conceptual framework to further develop behavioural theory on decision making in transport.

1.3 Assumptions and Limitations

At this point it becomes necessary to become conceptually specific about the two main subjects of this thesis: travel behaviour as the basic constituent of traffic flows and IVHS systems. It will be shown that travel behaviour encompasses a broad range of behaviours. Also, it will be shown that numerous and diverse IVHS systems are under development. For the purpose of this research it therefore becomes necessary to limit the definitions of travel behaviour and information systems which we will study.

This section addresses the decisions that were made on the scope of travel behaviour under consideration and the types of information systems for which a methodology will be developed. Before attention is directed to travel behaviour and information systems, some remarks on the type and scale of the network for which the proposed model must be suited, will be made.
Hamerslag & Van Berkum (1992) showed that the layout of the infrastructure, i.e. the network, influences the quantity of beneficial effects that may be expected from information systems. They estimated that the decrease in car kilometres due to information in urban networks would be larger than the expected decrease in regional networks. In the same line, it may be expected that the characteristics of the users of this infrastructure are related to the quantity of beneficial effects. Drivers who are familiar with the network may have less benefits from an electronic map than unfamiliar drivers. Also, drivers who are familiar with the network may benefit more from congestion information than unfamiliar drivers. Because both infrastructure and user characteristics seem related to the quantity of effects of information systems, evaluation of a limited number of field trials in which information systems are implemented, will not suffice. To estimate effects of information systems in various environments modelling approaches become inevitable.

The scale of the infrastructure for which such a model can be implemented, is primarily limited by computational and data collection and data storage considerations. This means that conceptually, the model will be extendable to any feasible network. The same limitations are valid for the driver population that can be modelled.

Travel Behaviour
In the field of transport modelling two main approaches to define and study travel behaviour can be distinguished (e.g. BGC, 1989; Goodwin, Kitamura & Meurs, 1990; Kitamura, 1988). The first approach departs from the trip as the basic and central unit of research. Each trip is considered separately, with its associated characteristics like origin, destination, departure time, arrival time, route, mode and purpose (Wilson, 1974). The second approach arises from the understanding that travel behaviour is a derived demand, resulting from the desire of people to participate in various activities (Van der Hoorn, 1989). In this approach trips are considered to be derived from activities. Generally, the trip approach can be understood as a subset of the activity approach.

The choice between the two approaches must follow from the ultimate research goal. For modelling purposes, the practicality of the approach is important. Clearly, the activity approach is theoretically the more complete of the two. However, it is also the most complex foundation. Although it is relatively easy to collect data on trip making behaviour, data collection on activity schedules, activity planning and rescheduling behaviour is arduous. Further, the motorist information systems under consideration are aimed at influencing route choice and travel timing behaviour, and not activity patterns. Moreover, most current models on travel behaviour are based on the trip approach. Because of this, but even more because of pragmatic reasons, that is, to restrict the complexity
of the modelling effort, we limit ourselves to the trip approach. From this choice some restrictions follow. These will be discussed next.

The most straightforward model resulting from the trip approach is the classical four stage model (Hamerslag, 1972; Wilson, 1974). In this model the four stages under consideration are trip generation, trip distribution, modal split and trip assignment. In the Netherlands it has become common to integrate modal split and trip distribution (Hamerslag, 1972) and trip assignment (Van Berkum, Hamerslag and Meurs, 1989) into one simultaneous model. Also trip generation can be modelled simultaneously (Hamerslag, 1980).

The model defines the output of these stages on an aggregate level. So, in the classical four stage model, individual travel behaviour is in fact irrelevant. Since we aim to estimate the effects of information on individual travel behaviour, it becomes necessary to scale down to a non-aggregate level of modelling.

To translate the four stages of the aggregate model to an individual level, while adding the time dimension, five individual choice processes become relevant:

a) generation choice;
b) destination choice;
c) mode choice;
d) route choice;
e) departure time choice.

The generation choice process, that is, the decision to make a trip, is basically ruled by the activity schedule of the individual. Some activities are rather compulsory, like work and school. Others are optional, like going to the movies and family visits. Clearly, activity patterns of different individuals may be interrelated, due to interrelations between individuals, e.g. in families and social networks, and to societal patterns, e.g. working hours and opening times of facilities.

The destination choice problem is important in a different way. Many activities are carried out outside of our homes, but we may sometimes have the option to choose from different locations where the same activities may be carried out. We may do our shopping in a nearby supermarket or drive to a shopping mall further away.

The mode choice problem is certainly important in relation to the expected benefits of information systems. Alleviation of congestion and pollution may be achieved not only as a consequence of improved driver route choice and timing decisions, but also as a consequence of modal shift. There are numerous reasons why an individual would choose a specific mode for a certain trip. Mode ownership, mode availability, the fact that certain activities require specific modes are but a few of these reasons (Onnen, 1989; Onnen & Van Knippenberg, 1989). To encompass mode choice processes in this research would make it necessary to include these aspects in the model as well. At this point we feel
it is necessary to let the methodology not become too complex, and exclude mode choice.

Although we admit that all five processes are relevant to travel behaviour, we have limited the scope of this thesis to the last two processes: route and departure time choice. This was done because of three, primarily pragmatic reasons:
- the historical background of this work, i.e. the DRIVE EUROTOPP project (see preface)
- the rapidly increasing complexity of the model when other processes are included
- the availability of data to validate the model.

Concerning the necessary data for the model in general, a fixed activity pattern with known destinations for each individual in the dataset will be assumed. From such a fixed activity pattern a trip pattern can be derived. For this pattern route and departure time choices are unknown. The model is designed to predict these choices.

In summary, travel behaviour in this research encompasses route and departure time choice processes. The aim of this thesis is to develop a methodology to predict the effects of various new information systems on route choice and departure time choice. In the next paragraph we will become more specific about what is meant by information systems.

Information Systems
Because of the large number and diversity of IVHS applications, it seems impossible to develop a single methodology to predict all of their effects. Furthermore, we have already decided to focus this research on route and departure time choice of car drivers. The type of information systems under consideration are therefore restricted to systems that were developed specifically for car drivers and that provide information which is relevant to these choice processes. Such information may influence higher tactical and strategic levels of decision making, i.e route planning and choice and departure time choice (Michon, 1985).

This thesis is concerned with the effects of traffic information generated and provided by new information systems. Of course, without these, drivers already have access to traditional information from paper road maps, radio broadcasts

2 In appendix C however, a model study is reported on what, in the long run, the influence of better information on network performance will be. Here, the influence of a changing perception of travel times on both destination choice and spatial distribution of activities is studied. Yet, in that chapter information is regarded as an abstract quality, and not as a result of a specific information system.
and from person to person. No driver can make route or departure time decisions without access to information which allows generation of expected - though maybe inaccurate - travel times, distances or other travel circumstances. These expectations may also be derived from mental maps drivers have of the transport system. The relevance of traditional ways of information dissemination is clear to us, but the focus of the present research will be on new information technology. In the future, integration of traditional ways of information dissemination may be necessary, but this will not be attempted here. However, this does not mean that drivers will be assumed to be completely ignorant about the network or prevailing travel conditions. Their initial expectations are certainly included in the proposed methodology.

Generally, a single information system may provide different types of information, for instance motorist, public transport and parking information. From systems that support different types of information, only those features dealing with route and timing information are considered.

Route and timing information may be either of a prescriptive or descriptive nature. Systems may be located either at home, in the office, in the vehicle, or at the roadside. Information from these systems may be transmitted visually, either in graphical or text format, or verbally through human transmitters or by synthesized speech. A comprehensive description of systems will be given in Chapter two.

The restriction to route and timing information implies that a number of systems that were developed for car driving and car traffic control will not be considered. First, systems designed for the automation of vehicle control are not included in this research. Such systems provide support for operational and lower level tactical tasks such as speed control, manoeuvring, lane-keeping, collision avoidance etc. These systems are expected to influence route and departure time choices only to a very small degree.

Secondly, parking information systems will not be considered. Though parking information may influence route choice and timing decisions, it is expected to be primarily supportive to the destination and mode choice processes. Parking information may specifically influence the exact destination of a trip. For instance, if drivers go shopping in a city centre, parking information may influence the location where they park their car within the city centre, but it will influence their shopping destination as such to a lesser extent. Parking information may also influence mode choice. If parking facilities are unavailable or use of these facilities is expensive, drivers may use public transport or park & ride facilities. However relevant, these choice processes are not part of this research.

Thirdly, systems that were designed only to allow authorities or fleet owners to manage transportation systems, e.g. fleet management systems and dispatching systems, and traffic control systems, e.g. signal optimization systems, incident
detection systems and highway and corridor control systems, are not part of this research.

The distinction between the functionality of different systems is not always completely clear. From the point of view of authorities variable message signs may be viewed as a highway and corridor control tool, while these may also be seen as motorist information systems. The main distinction between traffic control systems *pur sang* and motorist information systems, is whether the information that is provided allows drivers a certain amount of decisional freedom to comply with it. For instance, incident detection as such does not influence driver behaviour. Only when incident information is translated to road user advice and consequently transmitted to drivers, may route and departure time choices be influenced. In that case, some other motorist information system will be present. Clearly, assessment of the effects of such systems is included in this research. Another example is signal optimization, which may certainly influence route choice in urban areas. Due to optimization techniques certain routes may structurally become shorter or longer. If due to such changes route choice is influenced, this may be modelled more traditionally, because in that case changes in the fundamental properties in the network are evident.

Both the approach to travel behaviour and the information systems under consideration may seem limited in scope. We feel that these limitations are necessary. This research will show that the development of a dynamic model for route and departure time choice in information environments has already great conceptual complexity. Though the diversity of information systems which will be addressed is limited, a large number of different systems is still considered as will be shown in Chapter 2. More importantly, since more multifarious models seem to suffer in many cases from problems of validation, let alone implementation of the model due to the unavailability of the necessary data, we decided on a more restricted approach.

1.4 Outline of the Thesis

This paragraph will outline the main structure of the thesis.

Chapters 2 to 4 provide the reader with the basic, necessary theoretical background to understand the development of the methodology. Chapter 2 provides an overview of existing and currently developed motorist information systems within the definition arrived at in section 1.3. The main emphasis in discussion of these systems will be on the information that can be gained from them from the perspective of the individual user. The overview concentrates on the functionality of the systems and will not elaborate on technical details, such as hardware specifications. Insights from this chapter will serve to integrate the diverse types of information in the methodology that will be developed.
Chapter 3 provides an answer to the question whether and in what way current traffic assignment modelling techniques can and do address environments with and without information systems. The chapter discusses the current state of traffic assignment modelling techniques. Of course, emphasis lies on the relation between route and departure time choice and information on the one hand, and traffic assignment on the other. For each technique discussed the basic assumptions and limitations will be summed up and conclusions for the development of the present methodology will drawn.

Chapter 4 will elucidate the importance of the major constituents of the dynamic behavioural decision process which shapes travel behaviour. The chapter provides an outline of travel behaviour as (dynamic) decision making. Special attention will be directed to the role of uncertainty and incomplete knowledge in the decision making processes. Also, the importance of habit and attentional processes will be discussed in this context.

Chapter 5 forms a bridge between theory and application. This chapter summarizes the findings of the previous three chapters. Main conclusions will be drawn and assumptions and hypotheses on how to define the proposed methodology will be depicted.

In Chapter 6 the proposed methodology is presented comprehensively. The chapter describes in what way the different assumed choice processes are finally modelled. This chapter is divided into two parts. The first part allows readers with limited mathematical knowledge to understand the structure of the model and gives a mainly verbal description of its algorithms. The second part of the chapter provides a comprehensive mathematical specification of the model and its algorithms.

In Chapters 7 and 8 the validity of the methodology for two types of information will be addressed. In Chapter 7 data are used from a longitudinal panel study carried out on the ringway around Amsterdam, where a variable message sign provides route choice information. In this chapter also a parameter estimation procedure will be presented which is based on maximum likelihood. This procedure was developed specifically to estimate all relevant model parameters, because no existing, standard estimation procedures were available for this purpose. In Chapter 8 data are used from two laboratory experiments on route choice in a setting with and without information from a variable direction sign. The same estimation procedure as in Chapter 7 was used.

It must be noted that a validation of the methodology to model departure time choice will not be part of this thesis. The sole reason for this is that no data were available to us to carry out such a validation.

In Chapter 9 the conclusions from our research and their implications are discussed. The applicability of the methodology is examined and its usability as a decision maker's tool is considered. Finally, future directions for research and model development are given.
Motorist Information Systems

2.1 Introduction

The development of a methodology to estimate the impact of different, new information systems for car drivers, demands a clear understanding of the nature of motorist information. For our purpose not all types of motorist information are relevant. In the previous chapter we have already excluded a number of information systems. The focus of the present chapter and our research in general is on new, electronic information systems, which aid drivers to carry out the route and departure time choice tasks. In this chapter we will present an overview of those newly developed motorist information systems. Before we do so, a more general discussion of the motorist information under consideration is necessary. The aim of this discussion is to point out those aspects of information that can be relevant for the development of the methodology.

It is hard to discuss motorist information without reference to the receiver of this information and the circumstances for which the information is meant to be valid. Moreover, understanding the interplay between user, environment and information is crucial to the understanding of the potential effectiveness of motorist information. The aims of this chapter then are to provide understanding of this interplay on the one hand, and to provide a general overview of the information systems under consideration.

In this chapter motorist information will first be discussed without reference to actual information systems (Section 2.2). A number of relevant aspects of and distinctions between different types of motorist information will be introduced. From this it will become clear why it is not possible to address motorist information in a general way.

A detailed technical description of systems, and how they actually generate and present information is beyond the scope of this thesis. Furthermore, the proposed methodology should not include technical design specifications as
input parameters, since this would make the model susceptible to the rapid technical developments in the field, which is clearly unwanted.

A general overview of motorist information systems will be presented in Section 2.3. The core of all these systems is the information they can provide to motorists and the discussion therefore focuses on functionality.

2.2 Motorist Information

One of the primary aims of the motorist information under consideration is to reduce uncertainty and ignorance about route and timing options. Reduction of uncertainty and ignorance is expected to lead to improved route and timing choices. It will be assumed that information makes it possible for the motorist to order route and timing options on some preference scale in a more valid way, thereby allowing easier and more efficient choices. The degree to which information succeeds in reducing uncertainty and ignorance, depends on a number of factors, which may be conceptualized within the triad: information system - traffic system - user. Motorist information may be defined as a description of (properties of) components of the traffic system. The traffic system itself can be characterized by (dynamic) states, which reflect its partly unpredictable nature. The last element of the triad represents the user's knowledge and expectations, or conceptualization of the traffic system. The triad will be discussed more thoroughly in the following sections.

From the above, "net information" may be defined as the difference between the description of the traffic system by the information system, and the knowledge of and expectations about the traffic system motorists have. If this difference is positive, motorists would admit they have received information. Also if user knowledge is inconsistent with the information from the system, information may be transmitted. Depending on the credibility of the information system motorists may update their knowledge and expectations. The "net information" of a fixed piece of information will thus vary for different users according to their current knowledge and expectations. There are several possible reasons for the existence of differences between the user's knowledge and expectations, and the information system (which reflects the actual state of the traffic system with a certain credibility). Both information from the system, and user's knowledge and expectations may be false, unreliable or incomplete, or information may pertain to a different state of the traffic system than knowledge and expectations do. From this it must be clear that a sensible discussion of motorist information without reference to all elements of the triad is impossible. Each element of the triad will now be addressed in more detail.
Information
Motorist information describes the traffic system in different ways and may vary on a number of aspects: e.g. the nature or contents of the information, timing and place of dissemination, quality of the information, and the temporal horizon of the information.

The nature of information on routes and timing may be divided in two: (i) descriptive information and (ii) prescriptive information. Descriptive information provides drivers with information about the lay-out or state of the network or transport system (e.g. "congestion before Coentunnel", or, "Deventer-Amsterdam: expected travel time 1 hour and 50 minutes using A1"). Descriptive route information can for instance be provided by electronic road maps and city plans, tables with (expected) travel times and congestion, road lengths and other road characteristics, and other traffic and weather reports. Likewise, descriptive timing information may consist of reports on the (expected) travel time on routes during certain time frames.

Prescriptive route information tells drivers what to do, e.g. 'turn left at next intersection'. This type of information is similar to a co-pilot who directs the driver through the network. Such information relieves the driver to a large extent of route planning and route following tasks. Likewise, prescriptive timing information tells the driver to depart from his origin at a certain time, c.q. to postpone his departure. Of course, such information can only be provided before the actual trip is made.

Of course, descriptive and prescriptive information may be mixed ("major congestion ahead, destinations Rotterdam use A2"), in which case the given advice is motivated. Unmotivated prescriptive information may be either followed by the driver or ignored, depending on its credibility and relevance. On the other hand, plain descriptive information does not lead to compliance, but leaves it to the traveller to process this information and base a choice on it. Both types of information may lead to adjustment of the knowledge and expectations of the traveller.

The time at which the motorist receives information is related to the location of the information source. The main distinction is whether the information is provided in the vehicle (this includes road signs), thus allowing continuous information reception during the trip, or at home or in the office (pre-trip information), in which case information reception stops immediately on departure. Whether the information is up-to-date, sometimes depends on the location of the information source. For instance, a radio traffic report consulted at home before the trip may be invalid 15 minutes later when the driver is en route, because of changing traffic conditions. So, the moment of information transmittance is linked to the different types of dynamics present in the transport system (see Chapter 3). Though essentially almost all travel related information may be conceived as dynamic, some information may, for our purpose, be
understood as static, meaning that this type of information need not be updated frequently. Maps of road networks and free flow travel times are examples of such information. This type of information lends itself well to be disseminated by pre-trip information systems. Also, what has been called historical information (e.g. Ben-Akiva, de Palma & Kaysi, 1991) or time-dependent travel patterns within a given day (Mahmassani, 1989), which describe the state of the transportation system during previous time periods, may well be made available through pre-trip information systems. Though actual or current information, which informs drivers about day-to-day and real-time dynamics, as well as predictive information, can be delivered by pre-trip information systems, reliability of this information will often be smaller and its relevance more uncertain. This is so because sometimes the state of the transport system will be unstable and unpredictable over a longer time period, which makes the relevance of the information highly dependent on the actual position of the traveller at a certain time. In-vehicle or road-side information systems are indispensable to deliver these types of information with sufficient quality to drivers.

Quality of information may encompass a number of things: reliability, validity, and credibility. For system designers reliability and validity may be the most important quality criteria, for system users credibility could be the most important. Credibility of information is expected to play an important role in how many drivers comply with the advice, or adjust their behaviour accordingly.

Information may also vary in specificity. Specificity here refers to the degree to which the information indicates the precise location and time for which the information is valid. For instance, a driver may be informed only that a certain route is congested, or the report may be more precise by pointing out that a certain delay in travel time is to be expected on that route. The information may also vary in preciseness about the location of the congestion or route(s) for which the delay is valid.

Temporal aspects of information have to do with the time frame on which the information is based. Concerning temporal aspects, motorist information falls into one of three categories (Ben-Akiva, De Palma & Kaysi, 1991; see also Koutsopoulos & Lotan, 1999): (a) historical information; (b) current information; or (c) predictive information. Historical information describes the state of the traffic system during previous time periods. Current information equals the most up-to-date information about the prevailing traffic conditions. Finally, predictive information concerns expected traffic conditions during subsequent time periods. This last type, is necessarily generated by predictive computing algorithms. Such algorithms will use both historical and current information to predict the future state of the network. The reliability of these types of information depends on the states of the traffic system they relate to.
Generally, this reliability will be better for less dynamic (i.e. more predictable) network states than for more dynamic ones.

The various types of information may influence the knowledge state of the driver before the journey. In that case the decision process itself may be affected immediately. Information received during the trip may influence the knowledge state immediately and hence travel behaviour may be altered for the remainder of the trip. In both cases the knowledge state will change again after the trip has been performed due to the experienced trip. This in turn may affect the decision process for next journeys.

Information on routes and trip timing can thus be classified according to a number of different aspects. We have distinguished motorist information by its nature (descriptive versus prescriptive information), by the location of the information source (e.g. at home or in-car), by its quality, and by the time frame for which the information can be valid. Some of these aspects are interrelated and all may influence the way in which users respond to the information.

We will now turn to the traffic system, which the information is about.

Traffic system
A certain part of the traffic system can be in one of three states: (a) steady state, free flow; (b) steady state, with recurrent congestion, and (c) non-recurrent congestion and incidents.

Under steady state, free flow conditions demand in the network is less than supply. Under these circumstance, optimum route algorithms can provide "best" route information. Under such circumstances timing information is generally not necessary, because it follows immediately from the travel time.

In situations with recurrent congestion, demand exceeds supply in a more or less predictable way. In these situations expected travel times on routes vary in time, so timing information may be helpful. It seems that drivers can become very experienced with such situations, and use temporal variations in expected travel times to base their route and timing decisions on. E.g. drivers may be aware of the fact that certain parts of the network are only congested during peak hours. Less experienced drivers may find congestion unpredictable.

The most unpredictable situation arises from non-recurrent congestion and incidents. In these situations knowledge of free flow travel times will hardly be of any help, because travel times are erratic. Only one specific kind of knowledge, that is knowledge of the structure of the network, is useful because it allows drivers to select alternative routes. Of course, the advantage of structural knowledge applies also to the other states.

The described states of the traffic system also pertain to the dynamics of the system. The free flow state is essentially a non-dynamic state, since a description of this state may remain valid for a very long period.
Traffic dynamics in the transport system may be divided into three (Mahmassani, 1989): (a) time-dependent travel patterns within a given day; (b) day-to-day dynamics in travel behaviour; and (c) real-time dynamics. The first type of dynamics is concerned with the build up and dissipation of congestion in the network, and mainly results from societal travel patterns caused by restrained activity patterns, e.g. due to working hours, and by limited road capacity. These patterns result in recurrent congestion in certain parts of the network. The second type consists of day-to-day dynamics of user decisions as a response to experienced congestion and exogenous information. The third type is concerned with the flow patterns that result from the real-time decisions motorists make in the network, as a result of prevailing traffic conditions, as well as to supplied information of varying form, type and reliability. The last two types are less predictable than the first. If these dynamics lead to a situation in which demand exceeds supply, this will cause non-recurrent congestion.

From the above discussion of the traffic system it follows that motorist information on routes and timing will be directly related to the various states and dynamics within the traffic system. It seems likely that the more dynamic and unstable the traffic system is, the more need users will have for information.

Users

Users are by far the most complicated element of the triad. In fact, the sum of users in a network equals the traffic system. Traffic information can thus be viewed as a description of the behaviour of a number of network users. To complete the discussion of the triad this section will only briefly address the user since a more comprehensive discussion of the decision-making processes of motorists will follow in Chapter 4.

For motorist information to be beneficial to a user, this user must be, at least partly, uncertain or ignorant about some aspects of the traffic system. The distinction between uncertainty and ignorance is not a matter of degree. Drivers may very well know how to get from one point in the network to the next and may even have a general idea about travel times, but they may be uncertain about to be expected travel times or congestion on routes between these points during a certain time frame. In such cases drivers are uncertain about some properties of the network, although their knowledge of the structure of the network may be complete. Some drivers may not know how to get from A to B at all. These drivers are ignorant about properties of the network. Thus, their knowledge of the structure of the network is incomplete, i.e. they do not know that certain routes exist. It is clear that drivers who are completely ignorant, for instance tourists, will have different information needs than taxi drivers in the same city. A tourist may be satisfied as soon as the information allows him to find his destination, while taxi drivers may primarily want to avoid congestion.
The degree to which drivers are ignorant and uncertain depends on their experience with travel in the network, their experience with information (systems) and the traffic dynamics in the network. Therefore, ignorance and uncertainty are also dynamic concepts. We will return to this in Chapter 4.

We have discussed motorist information within the context of the triad traffic information - traffic system - user. We have stated that the last element of the triad, the user, is the most complicated one. We have indicated in what way the elements are interrelated, and we have elaborated on some important characteristics of each element. The purpose of the discussion has been to identify the aspects of motorist information that can be important for the specification of the aimed for methodology. In Chapter 5 we will return to this.

In the next section we will discuss the current state of the motorist information systems or IVHS under consideration.

2.3 Motorist Information Systems

Many people still assume that new traffic information technology is science fiction. This is not true. The major aim of this section is to provide readers with a basic overview of the current state of newly developed motorist information systems.

Some excellent overviews of IVHS technology, c.q. motorist information systems exist (TRB, 1991a; TRB, 1991b; see also OECD, 1988 and Rijkswaterstaat, 1992). In the following brief descriptions of separate systems, most of the time no specific references will be given. Readers are referred to the overviews for such references.

It seems impossible to keep up with the developments in this field. The two-weekly appearance of the IVHS-America newsletter and the many conferences and workshops devoted to the topic illustrate how rapid these developments are. Hence, we cannot hope to be complete or completely up-to-date in this overview, though we aim to provide the reader with the essentials of the developments going on.

Numerous systems have been developed and are under development. To create a picture of the main differences between the newly developed systems the discussion will follow the arrangement as in Table 2.1. This arrangement is rather arbitrary and primarily based on the different means of information dissemination. Of course other arrangements can be equally valid (e.g. Westerman & Hamerslag, 1993). In the presentation of systems we will only occasionally mention differences between the possible types and contents of information these systems can provide to drivers. The point of the overview is to provide a general picture.
Table 2.1: Overview of motorist information systems

Electronic Route Planning and Information Systems
The most common route planning device are road maps. Paper maps can be used either at home or in the vehicle, though studying road maps while driving the car at the same time may be cumbersome, if not dangerous, especially in dense traffic. More recently, electronic maps have become commercially available.

Map information may be supplemented by pre-trip information, either based on real-time or historical data. Such information links minimum path computer algorithms to network databases. Minimum paths can be determined in terms of journey time, distance or costs. Examples of such devices are DriverGuide in the US, and the route planning service ROUTE, which is included in the French TELETEL videotext system. Also in France, the ANTIPOE teletext TV service contains maps showing congestion on major roads in selected areas. This information is updated at hourly intervals. In the U.K. a similar service exists, named ROADWATCH. At a pan-European level ATIS is being developed which is based around the existing ERIC (European Road Information Center). ATIS aims to provide pre-trip information on road traffic conditions and other aspects important to tourists.

Traffic Information Broadcasting Systems
Traffic information broadcasting systems have been known for a long time in most countries. In many cases traffic information is broadcast during or
in between normal radio programs. In the US and Japan Highway Advisory Radio (HAR) exists, which is a short-range broadcast service provided to motorists through standard AM car radios. The localized nature of this service makes it necessary to notify motorists by road signs when approaching an area serviced by HAR in order to tune their radio to the appropriate frequency. In Germany ARI (Autofahrer Rundfunk Information) was developed, which is widely used in Germany, parts of Austria, Switzerland and Luxembourg. The principal function of the ARI system is to assist drivers in tuning to a station providing traffic information and to alert drivers when a traffic broadcast is imminent. Recently, a more advanced version, ARIAM (ARI aufgrund Aktueller Messdaten) was developed. It uses automatic incident detection devices to reduce the delay between the detection of a change in the traffic conditions and the time the motorists receive information on this. In this way the reliability and validity of the information has been improved.

RDS (Radio Data System) will eventually supersede the ARI and ARIAM systems. RDS enables digitally encoded data to be superimposed on the stereo multiplex signal of a conventional FM broadcast. These data are decoded by an adapted car radio. Currently RDS-TMC (RDS Traffic-Message-Channel) is being tried out at different locations (Rhein-Corridor, Gotenburg, Canada, Hong Kong, Detroit). RDS-TMC requires a special receiver to decode the traffic information, which can then be either displayed as either text or synthesized speech.

Self Contained On-board Navigation and Location Systems
On-board navigation and location systems provide motorists with information on their current location and how this relates to their destination. In some cases advice on the best route to take is also provided. This information is calculated and displayed by a self-contained vehicle unit, which does not require a link to the roadside infrastructure. Self-contained systems are generally of most use in conducting the route following task. Systems providing actual guidance can also be used for the route planning task. However, without any information on real-time traffic conditions, on-board navigation systems can only reduce motorist inefficiency under steady state conditions.

A large number of such systems have been and are being developed in the US, Japan and Europe. They can be divided into three main types: (1) directional aids; (2) location displays; and (3) self-contained guidance systems. Directional aids typically use dead reckoning, using measurements made by distance and heading sensors to compute the vehicle’s progress from a known starting location. Mostly the heading is displayed by an arrow which identifies the direction the motorist should take in order to reach his destination.

The second type, location displays, shows motorists their current position on an in-vehicle display unit, frequently in the form of a point on an electronic map display. The advantage of location displays over pure directional aids is
that the actual road network is indicated by the system. However, location
displays do not offer advice on the best route to take. Most location displays
use dead reckoning, and to a lesser extent trilateration techniques. Examples
of these systems are the Honda ELECTRO-GYROCATOR, the ETAK
NAVIGATOR, TRAVELPILOT by Bosch, the Philips CARIN system (which
is further developed in the EUREKA framework as CARMINAT, combining
CARIN and RDS-TMC).

The last type, self-contained guidance systems, provides motorists with actual
routing advice as well as vehicle location information. To provide this routing
advice a more comprehensive description of the road network must be stored
in the vehicle unit together with an algorithm to compute an optimum path
through the network. As stated before, such a route advice cannot take into
account any real-time changes in traffic conditions, since it must rely completely
on historical information. Examples of self-contained guidance systems are
ROUTEN-RECHNER by Daimler-Benz, EVA (Electronic Traffic Pilot for
Motorists) by Bosch-Blaupunkt. In the 1970's such a system was developed
in the US under the name ARCS (Automatic Route Control System).

Externally Linked Route Guidance Systems
There exist a number of externally linked route guidance systems. These comprise
electronic route planning and route following aids that have a communications
link from in-vehicle guidance equipment to an external system providing network
or traffic information. The major advantage of these systems is that they can
potentially take account of real-time traffic conditions, thereby providing
additional benefit to the motorist in route planning and route following
performance. Two main categories can be distinguished: (1) systems that are
linked by long-range communications or a broadcasting channel to a traffic
information service and (2) systems with short-range communications to a
roadside infrastructure.

The first category is limited to receiving information about traffic incidents
and delays as reported by the police or highway agency personnel. Examples
are route guidance systems using mobile cellular radio, systems linked with
RDS-TMC and systems using digital broadcasting (for instance Advanced Mobile
Traffic Information and Communication System (AMTICS).

Systems with short range communications can be provided with either one-way
or two-way vehicle-roadside communications. Examples are the Electronic
Route Guidance System (ERGS) developed in the USA in the early seventies.
In Japan during the 1970's the Comprehensive Automobile Traffic Control
System (CACS) and during the 1980's the Road-Automotive Communications
System (RACS) were developed. In Europe several systems have been developed,
such as the German Autofahrer Leit und Informationssystem (ALI) by Blaupunkt
and AUTO-SCOUT by Siemens. Later Bosch, Blaupunkt and Siemens developed
ALI-SCOUT which was tested in the LISB trial (Hoffmann, Sparmann & Von
Tomkewitsch, 1991) in Berlin and the AUTOGUIDE trial (by Plessey Controls) in London (Jeffrey, Russam & Robertson, 1987). A trial was planned in Amsterdam with a further adaption of the system, now named EuroScout (Siemens).

Variable Message Signs
Roadside variable message signs (VMS) can be used for different purposes. In the Netherlands variable message signs are used to control speed and prescribe lane usage, but also as a medium to provide local congestion information. For example the "Route choice Information Amsterdam" system (RIA) alerts drivers of traffic conditions ahead to allow them to choose the best route (see Rijkswaterstaat, 1992). This last example of VMS is of particular concern to this work, and the reader should bear in mind that further reference to VMS will be to this kind of application (Figure 2.1).

Figure 2.1 The first Dutch variable message sign

Another type of VMS are variable direction signs. These signs provide flexible signposting and can be used for instance to divert traffic along less congested routes.
Conclusion
In the first part of this chapter we distinguished a number of relevant aspects of the traffic information under consideration. We distinguished descriptive from prescriptive information, and elaborated on the consequences of the time and place of information provision, and on the meaning of quality of information. Furthermore, we made clear that information has to do with the dynamics which are present in the traffic system. We stated that users are the most complicated element of the triad information - traffic system - users. We will return to users in Chapter 4.

In the second part of the chapter we gave an overview of information systems that were recently developed or are still under development. The main purpose of this was to show that new information technology has already been implemented, and to provide some examples of the information systems of which the effects must be modelled.
3

Review of Existing Modelling Approaches

3.1 Introduction

The objective of this chapter is to review the current state of assignment modelling with emphasis on route choice and, to a lesser extent, on departure time choice. The question will be examined, what parts of the existing techniques can be used to address our final goal: to assess the effect of information systems on traffic flows.

A transportation system can be divided into two parts: transportation supply and travel demand. The first is the set of facilities and means available to the users, e.g. the network. The second is represented by the users of the network. The interaction between supply and demand produces a flow pattern on the links of the network. A model that simulates this interaction is known as a traffic assignment model (See e.g. Sheffi, 1985). Typical processes in assignment models are route choice, departure time choice (only in dynamic models) and the actual loading of the network. These are also the processes of interest for our research goal.

In order to be able to present a review of existing modelling approaches we will distinguish different types. Three main distinctions are made: firstly, a distinction between static and dynamic approaches, secondly, a distinction between approaches that define an equilibrium situation and those that do not, thirdly, the distinction between deterministic and stochastic approaches. In both the deterministic and stochastic approach travellers are assumed to be rational, and to choose the best alternative. In the deterministic approach traveller are assumed to have perfect knowledge of the whole network. In the stochastic approach, some sort of unawareness or uncertainty about the properties of the network is allowed.

In Table 3.1 an overview of the different approaches that follow from these distinctions is presented. Each approach will be discussed in more detail to
make clear what parts of these approaches can be used for our purpose. In Table 3.1 the different approaches are abbreviated as follows. The first letter indicates whether the approach is static (S) or dynamic (D), the second indicates whether the approach is stochastic (S) or deterministic (D), and the third and fourth letters indicate whether the approach is oriented to solve a (user) equilibrium (UE) or not (NE).

Table 3.1 Overview of different types of assignment

<table>
<thead>
<tr>
<th></th>
<th>static deterministic</th>
<th>static non-deterministic</th>
<th>dynamic deterministic</th>
<th>dynamic non-deterministic</th>
</tr>
</thead>
<tbody>
<tr>
<td>no equilibrium</td>
<td>SDNE</td>
<td>SSNE</td>
<td>DDNE</td>
<td>DSNE</td>
</tr>
<tr>
<td>equilibrium</td>
<td>SDUE</td>
<td>SSUE</td>
<td>DDUE</td>
<td>DSUE</td>
</tr>
</tbody>
</table>

We will show that only some of these techniques are applicable to tackle our problem. Particularly, deterministic approaches cannot be used. Nevertheless, these will be discussed since deterministic techniques mostly serve as a foundation for stochastic techniques.

At this point it is necessary to elaborate on the term utility (Hammerslag, 1986). When an individual is contemplating going somewhere the fact that he will visit some destination obviously has some utility. The trip itself requires a sacrifice, an effort. The individual will have to spend time, and money to perform the trip. From economics it is known that he will only perform the trip if the utility of visiting the destination is larger than the effort needed for the trip. The problem is that the utility cannot be measured. Only the effort can be measured. In general the individual will choose the trip (route, mode, departure time) that yields minimum effort.

It is unfortunate that in most of the literature, the term utility is used for effort. Thus when there is talk of utility maximization, in reality effort minimization is meant. Sometimes this problem is overcome by defining disutility being negative utility. Obviously the term disutility is a mathematical artifact without any clear meaning.

However, it could be argued that utility maximization and effort minimization are equal if we mean by utility net-utility. Suppose we denote the utility of performing an activity at a certain destination with $N$, and $E$, the effort needed to perform this activity is a weighted sum of attributes (e.g. travel time, travel cost), sometimes referred to as generalized cost. The activity will only be performed if $E < N$. In general the effort can be minimized by, for instance, choosing the best route, so it can be stated that the activity will be performed if $N - \min E > 0$.

Usually the value of $N$ is not known and hard or impossible to determine.
Now suppose we define $U$ as the utility of the whole, i.e. the utility of performing the activity minus the effort that is needed. Thus $U = N - E$. If we assume that the value of $N$ is not influenced by $E$ we can state that minimizing $E$ is exactly the same as maximizing $U$. We will call $U$ the net utility, i.e. the utility that remains after subtracting the effort from the utility. Therefore it is valid to say that minimizing effort equals maximizing net-utility. So the term net-utility would be the right term instead of utility.

Still, to stay in line with existing literature we will use the term utility, being net-utility. We will also use the term utility maximization meaning net-utility maximization which equals effort minimization. We will do this although we are aware of the fact that this is not the correct use of the term 'utility'.

### 3.2 Static versus Dynamic Approaches

In static models network conditions, such as flows and travel times, do not vary during the reference period. So, in a static model all individuals base their decisions on invariant conditions. Obviously, this is a strong simplification of reality. Further, in static models trips are assigned to a specific route during the whole reference period. This means for instance, that when a peak period is modelled, the same cars can be present at the same time at two consecutive bottlenecks during the whole peak (Hamerslag, 1989). The properties of a static setting imply three main shortcomings:

- $i$ only route choice decisions can be examined
- $ii$ departure time choice is ignored
- $iii$ delays up and downstream bottlenecks cannot be modelled adequately.

These shortcomings may be overcome by introducing within-day dynamics into the models. Before we go into this, we will elaborate on the fundamental difference between static and dynamic models: the inclusion of the dimension time. This needs further explanation.

In transport modelling 'time' is used for three different purposes (Goodwin, 1989):

**Time as a resource**

Every journey involves the passing of time, and in economic approaches it is often convenient to treat time as analogous to money, i.e. it is 'spent' on the journey. Use of generalized cost is based on this idea. In general it will be an answer to the question how much time is involved.

**Time as an location**

Every event happens at a location in space and time. In general it will be
an answer to the question *when* or at *what* time.

*Time as a framework*

Using dynamic approaches, every process can be seen as an ordered sequence which takes place in time. An informal definition is:

'A dynamic model is one which considers the influence of what has happened at time \( t-1 \) on what happens at time \( t \), and the influence in turn on what will happen at time \( t+1 \).'

In general it will be an answer to the question *how long* does it take a cause to have effect.

So dynamics have to do with time-dependency. The existence of different time periods in a model by itself does not imply that the model is dynamic, unless events in one period can influence events in the next.

In assignment models two classes of dynamics can be distinguished: day-to-day dynamics, and within-day dynamics. Most dynamic assignment models deal with the last type of dynamics.

Some dynamic models do not address departure time. Departure time rates are fixed, but route choice is modelled in a dynamic way, so traffic flows at bottlenecks can be properly modelled.

In reality traffic conditions at the system level will vary, e.g. capacities can fluctuate due to adverse weather conditions. This uncertainty is a necessary, but not a sufficient condition to justify a dynamic framework. It was shown that this problem can be described within a static framework where each individual is perfectly informed about the 'rules of the game' (i.e. the exact performance of the network and the behaviour of other network users) and in which each user participates in an n-person game under uncertainty (Arnott, de Palma and Lindsay, 1991)

Also, uncertainty at the individual level exists, e.g. due to a varying demand. Individuals are not perfectly informed, and even if they were, they may not always choose the best alternative. These considerations imply that a more satisfactory approach would be a day-to-day dynamic model. Suppose we want to study a peak period. To take varying conditions within the peak into account a within-day dynamic model must be used, and when peak-to-peak variations in travel conditions must be taken into account a day-to-day dynamic model must be used.
3.3 Equilibrium versus Non-Equilibrium Approaches

The notion of equilibrium in the context of transport parallels the physical notion of equilibrium, which is the state in which there are no (net) forces that try to push a system to some other state. When a system is in disequilibrium, there are forces that tend to direct the system towards the equilibrium state. In transport modelling flows are pushed towards the equilibrium state by a route switching (or departure time switching) mechanism. At equilibrium flows will be such that there is no incentive for route (or departure time) switching (Sheffi, 1985).

In assignment models the situation of equilibrium is defined either from the road users’ point of view, or from the systems point of view. In both cases the equilibrium situation is an optimum, in the sense that a minimum cost situation is defined. This situation is not necessarily the stationary situation that may, for instance, occur in a day-to-day dynamic model. Stationarity does not equal the concept of an equilibrium. Stationarity is defined by the process while equilibrium is defined by the context.

From a user’s point of view the static deterministic user equilibrium (SD-EU) is the situation in which no user can improve his travel time by unilaterally changing routes (Wardrop, 1952).

The dynamic deterministic user equilibrium (DDEU) is the same as the static version (SDUE), except for the fact that the dimension time is added. This means that cars are not assigned to the whole route during the reference period but only to a link, during which time the car has to traverse this link. Also, to determine whether the chosen route can be improved, the dimension time is added. This is done by defining the travel time on a link as a function of traffic flow being a function of time. This means that the solution of a dynamic equilibrium is a time dependent flow pattern. From this flow pattern travel times can be derived, also in time.

Departure time can be added to the definition of the dynamic equilibrium. Further, a stochastic version of the dynamic equilibrium can be defined in a similar way as in the static model.

Similar definitions of equilibria can be given from a systems point of view, but in that case the total amount of travel time (or cost) in the system is minimal. These two equilibria are not necessarily the same, as was shown in Braess’ paradox (Braess, 1968) for static deterministic approaches.

3.4 Deterministic versus Stochastic Approaches

The deterministic approach to traffic assignment assumes travellers to be perfectly informed utility maximizers. They are assumed to have complete knowledge of the whole network. This means they have complete knowledge
of all routes: they know of their existence and they know all travel times, costs etc. This behavioural assumption is the core of all the deterministic models and implies traveller’s omniscience. Further, travellers determine the best alternative from utility maximization.

In stochastic models however, perceived knowledge is used. Usually this is modelled by a random utility model, where a stochastic error term is added to the utility of each alternative. Thus the omniscience assumption is relaxed.

3.5 Static Approaches

In this section it will be shown that static approaches cannot be used to address our research goal. Still, they will be discussed in detail, since they are the basis for dynamic approaches.

Static Non Equilibrium Approaches

Generally these approaches are not interesting for the application in this thesis. They will only be discussed rather briefly. Static approaches are the most simple and ignore congestion. The deterministic approach is adequately modelled by all-or-nothing assignment. All travellers are perfectly informed about the network, and supply is not influenced by demand. This means that all travellers between a certain origin-destination pair are assigned to the shortest route, which can be easily determined, e.g. by using Dijkstra’s shortest path algorithm (Dijkstra, 1959). In stochastic approaches not all travellers are perfectly informed, but still supply is not influenced by demand. For the route choice part a random utility model is usually used. Bovy has presented a complete overview of all existing methods (Bovy, 1990).

Static Equilibrium Approaches

To define the deterministic and stochastic static equilibria, traffic assignment is first defined as a mathematical program formulation (Sheffi, 1985). Both a network and an OD-matrix are used. Suppose each OD-pair \((o,d)\) is connected by a set of routes \(R\). Let \(q_{rd}^{od}\) be the flow and \(t_r\) the travel time from \(o\) to \(d\) along route \(r\) and \(t_a\) is the travel time on link \(a\) \((r \in R)\). Then it holds that

\[
t_r = \sum_a t_a \delta_{ar}
\]

(3.1)

where \(\delta_{ar} = 1\) when link \(a\) is on route \(r\) and 0 otherwise.

In the static deterministic user equilibrium no user can improve his travel time by unilaterally changing route. This definition was first put forward by Wardrop (1952) and assumes that all car drivers have complete and perfect
knowledge of the network and only want to minimize their travel time. Suppose that the OD-matrix $T$ is given, with $T_{od}$ indicating the number of trips from origin $o$ to destination $d$, then the solution of the static deterministic equilibrium can be obtained by solving

$$\min z(x) = \sum_{a} x_{a} \int_{0}^{x_{a}} tt_{a}(\omega) d\omega$$

subject to

$$\sum_{o} q_{r}^{od} = T_{od}$$

$$q_{r}^{od} \geq 0$$

$$x_{a} = \sum_{o,d,r} q_{r}^{od} \delta_{ar}$$

The solution-method of (3.2) s.t. (3.3) to (3.5) is discussed in Appendix B.

From the formulation of the static deterministic user equilibrium (SDUE), the stochastic version can be formulated by assuming that all trip makers do not have perfect knowledge of the network. Random utility choice models are used for route choice.

Let $U_{r}$ represent the perceived travel cost on route $r$, connecting $o$ and $d$. Obviously $U_{r}$ is a random variable. Let further $tt_{r}$ be the actual travel time on route $r$, connecting $o$ and $d$ and further let $\varepsilon_{r}$ be a random variable with mean 0. Assume as in random utility models that

$$U_{r} = tt_{r} + \varepsilon_{r}$$

Thus travel cost is defined as travel time. The share of drivers choosing route $r$ is

$$P_{r} = \Pr (U_{r} < U_{s}, \forall s \neq r)$$

Nota Bene:

$$\Pr (U_{r} = U_{s}) = 0 \quad \forall r, s \text{ with } r \neq s$$

Dependent on the chosen distribution of the random error term a specific choice model can be derived.

The static stochastic user equilibrium (SSUE) can be formulated as the solution of the following minimization program
\[
\min z(x) = -\sum_{od} T_{od} \mathbb{E}\left[\min_k \{U_k\} \right] + \sum_{a} x_a t_a(x_o) - \sum_{a} \int t_a(\omega) d\omega \quad (3.9)
\]

subject to
\begin{align*}
& (3.3) \text{ to } (3.5) \text{ and} \\
& q_{r}^{od} = T_{od} P_r \quad (3.10)
\end{align*}
With \( P_r \) being the probability of choosing route \( r \) when travelling from \( o \) to \( d \). The solution of this program is more simple than its formulation. The algorithm can be found in Appendix B.

**Conclusion**

The conclusion of this section is that all static equilibrium approaches assume only utility maximization as a decision rule. In the deterministic case omniscience is also assumed. Further, the formulation of both problems is flow oriented. In the deterministic case individual route choice does not matter, as long as the flow pattern is optimal. It is well known that the optimal flow pattern does not specify a unique solution for individual route choice (Florian, 1977).

Our research goal is to determine the impact of traffic information. Impact is both on an aggregate level (what are the effects on flows) and on an individual level (what are the individual benefits). Static equilibria are aggregate approaches. Individual behaviour is not modelled. Further, static models cannot describe temporal fluctuations and day-to-day adjustment of behaviour. To evaluate the impact of traffic information these are important issues, so static approaches cannot be used for our goal.

### 3.6 Within-day Dynamic Approaches

From the previous section it was concluded that static models cannot be used to address our problem. Dynamic approaches could at least solve one of the reasons for this, because they can describe temporal fluctuations of traffic flows.

In this section within-day dynamic approaches will be discussed. Day-to-day dynamics will be discussed in Section 3.7.

**Dynamic Deterministic Equilibrium Approaches**

Dynamic assignment models aim to predict the temporal evolution of traffic flows on a congested transportation network in which demand and supply vary over time. This is in contrast with static models that assume that demand and supply do not vary over time. Again two classes can be distinguished: the
dynamic user optimum, which minimizes individual travel cost and the system optimum, which minimizes total travel cost.

Time can be modelled as a discrete variable (i.e. the time axis is divided into intervals) which allows consideration of within-day period to period variations. Time can also be modelled as continuous variable, in which case the variations are the derivatives of the functions.

When time is discrete mathematical programming (MP) is used for problem formulation. Optimum control theory (OCT) is adopted when time is modelled as a continuum. Both approaches solve the problem from a flow point of view. This means that the problem is formulated such that a flow (as a function of time t) for all links in the network is the solution to the problem. These flows must obey the flow conservation law at each node in the network, but individual behaviour usually is not modelled. This implies that these approaches are less interesting for our research goal. For reasons of completeness they will, however, be addressed.

System optimum, MP-approach

The first attempt to solve the dynamic system optimum by formulating it as a mathematical program was made by Merchant (1974) and Merchant and Nemhauser (1978a, 1978b). Consider a fixed planning horizon \( \{0, t, \ldots, T\} \). The state of each link \( a \) in a network is described by the nonlinear difference equation that

\[
x_{a,t+1} - x_{a,t} = e_{a,t} - g_a(x_{a,t})
\]

(3.11)

where

- \( x_{a,t} \) the number of vehicles on link \( a \) in period \( t \),
- \( e_{a,t} \) the number of vehicles admitted on link \( a \) in period \( t \)
- \( g_a(x_{a,t}) \) the number of vehicles leaving link \( a \) in period \( t \). The function \( g_a \) is used to describe congestion conditions.

Further, the flow conservation law must hold for each node \( k \), so

\[
G_{kt} + \sum_{a \in B_k} g_a(x_{a,t}) = \sum_{a \in A_k} e_{a,t}
\]

(3.12)

where

- \( G_{kt} \) the number of vehicles generated at node \( k \) in period \( t \)
- \( A_k \) the set of links with tail \( k \)
- \( B_k \) the set of links with head \( k \)

Now, let \( K_a(x_{a,t}) \) be the cost that occurs on link \( a \), when the number of vehicles is \( x_{a,t} \) at the beginning of period \( t \). The Merchant-Nemhauser-model can be formulated as

\[
\min \sum_t \sum_a K_a(x_{a,t})
\]

(3.13)
subject to 
(3.11) and (3.12)
\[ x_{a0} = X_a \geq 0 \]
\[ e_{at} \geq 0 \]
\[ x_{at} \geq 0 \]

System optimum, OCT-approach

The idea of solving the problem using an optimal control theory (OCT) approach was introduced, and further researched by three people, Wie, Friesz and Tobin (Wie, 1988; Wie, Friesz & Tobin, 1989, 1990). First the Merchant-Nemhauser model was reformulated in 'OCT-format'. In the Merchant-Nemhauser model \( t \) is defined as a continuous instead of a real variable. That means that all instances where a constraint was defined with \( t = 1, \ldots, T \), it alters to \( t \in [0, T] \). All variables become functions of \( t \) and difference equations become differential equations.

User optimum, MP-approaches

Janson (1992) presented a bi-level programming approach that had been already used before by Leblanc and Boyce (1986) for optimal network design problems. The formulation needs two subproblems, an upper sub-problem (UP) and a lower sub-problem (LP). The formulation is very complex. For understanding the idea behind the solution only the upper sub-problem, that is the dynamic equivalent of (3.2) is necessary. It is:

\[
\text{(UP)} \quad \min \sum_a \sum_t x_{at} \int_{0}^{x_{at}} t\tau_a(\omega) \, d\omega
\]

subject to the obvious dynamic flow conservation laws. In this formulation \( t\tau_a(\omega) \) denotes the travel time on link \( a \) at time interval \( t \).

Hammerslag (1989) developed a heuristic for the problem of dynamic assignment. It basically follows the MP-approach as presented by Janson. The approach follows the solution algorithm that was developed for the static user equilibrium. The dimension time was included in the route choice module. This means that the shortest route is determined, taking into account the temporal flow pattern on each link. It is currently the only method that can handle large networks. A further advantage of this approach is that, due to the fact that it is similar to the static user equilibrium, it can be integrated into larger modelling framework of which trip distribution models, departure time choice models or land-use models are part. Because of the heuristic approach, it cannot be proved that an equilibrium is determined. Further, the model assumes travellers' omniscience and that travellers are only utility maximizers.
The first version of the heuristic does not deal with departure time choice. The basic idea behind the heuristic is the same as was used in the traditional static deterministic user equilibrium. However, the all-or-nothing (AON) assignment used in that approach is substituted by a procedure that determines shortest routes in time. AON-assignment in time yields a density $\rho_{at}$ for all periods $t$ and links $a$. In the original version a flow-update procedure was used as in the static equilibrium solution. Van Groel (1992) used density instead of flow. In this manner the build-up and decay of queues can be described more adequately. This rule is

$$
\rho_{at} = (1-\lambda)\rho_{at}^{old} + \lambda\rho_{at}^{new}
$$

(3.15)

The parameter $\lambda$ is fixed as either 0.2 or $1/(1+\text{iteration number})$. This is unlike the solution of SDUE where $\lambda$ is determined optimally as a solution of a mathematical programming sub-problem.

A second version was developed in which the departure time choice process was included (Kroes and Hamerslag, 1989). The time axis was first divided into a number of departure time intervals. A traditional logit model was used to choose between the departure time intervals.

$$
\Pr(t) = \frac{e^{U_t}}{\sum_p e^{U_p}}
$$

(3.16)

with

$$
U_t = \beta_1 (tt_t - tt) + \beta_2 \left| \tau_p - \tau_t \right|
$$

(3.17)

where

- $tt_t$ total travel time departing in interval $t$
- $tt_p$ total travel time departing in desired interval $p$
- $\tau_t$ mean of departure time interval $t$
- $\tau_p$ mean of desired departure time interval $p$
- $\beta_1, \beta_2$ parameters

User optimum, OCT-approach

First the instantaneous user equilibrium is defined. This defines a situation in which drivers have complete information of the current state of the network, but no information about the network conditions they will encounter when they move downstream.

Let $D_a[x_a(t)]$ be the instantaneous cost that occurs on link $a$, when the number of vehicles is $x_a(t)$ at the beginning of period $t$. Then the OCT-formulation of the dynamic instantaneous user optimal assignment becomes (Wie, 1988; Friesz et al. 1989)
\[
\min J_2 = \sum_a \int_0^T \int_0 [D_a(\omega) \frac{dg_a(\omega)}{d\omega}] d\omega \ dT
\]

subject to

\[ [x_a(t), u_a(t)] \in \Omega \]

where \( \Omega \) is the feasible set. When the instantaneous constraints are relaxed, Friesz et al. (1989) showed that this problem also has a OCT-formulation.

**Dynamic Stochastic Equilibrium Approaches**

As in the static case, in the dynamic setting also the stochastic nature is modelled by means of a random utility maximization process. Yet, in a dynamic environment another choice dimension occurs, namely departure time. Ben-Akiva & De Palma (1986) suggest a sequential decision making process.

Each individual is assumed to decide first what time to depart and then, conditional on this choice, which route to follow. So the probability \( P_r(t) \) that, between a certain origin and destination, route \( r \) and departure time \( t \) are chosen is expressed as

\[ P_r(t) = \text{Pr(departure time } t \text{)} \cdot \text{Pr(route } r \text{ given departure time } t) \]

Adopting the concept of a mixed discrete/continuous nested logit (Ben-Akiva & Lerman, 1985) it follows that

\[ P_k(t) = \frac{e^{\mu_k V_{s,t}(t)}}{\sum_k e^{\mu_k V_{s,t}(t)}} \frac{e^{\mu_r V^*(t)}}{\int_{T_0}^{T_0+T} e^{\mu_r V^*(u)} du} \]  \( (3.19) \)

where

- \( V_{k,r,s}(t) \) the measured utility experienced by a driver travelling from \( r \) to \( s \), departing at time \( t \) using route \( k \)
- \( \mu_r, \mu_r \) scale parameters associated with the two choice processes
- \( V^*_{r,s}(t) \) a composite variable which expresses the expected maximum utility from the choice among feasible alternative routes at time \( t \). It is defined as the log-sum

\[ V^*(t) = \frac{1}{\mu_r} \ln \sum_k e^{\mu_r V_{s,t}(t)} \]  \( (3.20) \)

A travel time model must be used in order to determine the utilities. The formulation, however, then becomes so complex that analytical methods do not yield a solution. Only when using a demand adjustment process, by simulating a steady state, can an equilibrium presumably be established.

The above concept was combined with day-to-day adjustment procedures...
as described in Section 3.7 for a general network application by Vythoulkas (1990)

The concept of sequential decision making can be challenged. In reality these choice processes are likely to occur simultaneously. Also the fact that through the sequence for departure time a logsum must be used is questionable. The impact of a 'bad' route may become large, while in reality this route would never be considered for a specific departure time.

**Conclusion**
The conclusion of this section is that all dynamic approaches assume only utility maximization, and, except for the approach suggested by Ben-Akiva et al. (1986), all approaches are flow oriented. Most dynamic approaches do not deal with *individual* route or departure time choice. So these approaches also cannot be used for our purpose.

The approach by Ben-Akiva is promising, since both choice processes are modelled explicitly. Only the sequential order of departure time and route choice is questionable. A further problem is that this model does not take individual expected utility into account. This makes it hard to integrate this concept immediately in an information environment. A major problem is that it is practically unsolvable.

In this respect it is worth mentioning that, although it cannot be proved that the heuristic yields an equilibrium, the approach by Hamerslag is currently the only approach that can handle large networks. Further it could easily be made stochastic by adding an error term as is done in static equilibrium approaches.

### 3.7 Day-to-Day Dynamic Approaches

**Route choice**
Dynamic day-to-day route choice models are mainly based on the approach presented by Horowitz (1984) for a two link network. Suppose

- $q_{at}$ the traffic volume on link $a$ (since the network has two links, and two routes, link and route may be interchanged) and day $t$.
- $ett_{at}$ measured travel time\(^1\) on link $a$ on day $t$.
- $U_{at}$ perceived cost on link $a$ on day $t$.

Three types of information gathering processes are considered. In all processes decisions are based upon experiences of the previous days.

\(^1\)In this setting travel cost is defined as travel time. More generally travel time is an attribute of travel cost.
Model I
Route choice decisions over time are based on weighted averages of measured travel costs in previous periods. So,

\[ U_{at} = \sum_{k=1}^{t-1} w_k(t-1)ett_{ak} + \varepsilon_{at} \]  

(3.21)

\( \varepsilon_{it} \) is a random variable distributed independently of \( t \), the weights \( w_k \) are non-negative and it holds that

\[ \sum_{k=1}^{t-1} w_k(t-1) = 1 \]  

(3.22)

For all \( a \) and \( t \), \( \overline{ett}_{a,t-1} \), the weighted mean, is defined by

\[ \overline{ett}_{a,t-1} = \sum_{k=1}^{t-1} w_k(t-1)ett_{ak} \]  

(3.23)

A traveller chooses link 1 in period \( t \) iff \( U_{1t} < U_{2t} \).
The probability of this event is \( P_1(\overline{ett}_{1,t-1}, \overline{ett}_{2,t-1}) = F(\overline{ett}_{2,t-1} - \overline{ett}_{1,t-1}) \).
So the flow at \( t \) on link 1 is \( Q_{1t} = F(\overline{ett}_{2,t-1} - \overline{ett}_{1,t-1}) \).
Further a link-performance function is defined by:

\[ ett_{at} = \mu_a(Q_{at}) \]  

(3.24)

Model II
Route choice decisions over time are based on weighted averages of perceived travel costs in previous periods. So,

\[ U_{at} = \sum_{k=1}^{t-1} w_k(t-1)(ett_{ak} + \varepsilon_{ak}) \]  

(3.25)

and

\[ \sum_{k=1}^{t-1} w_k(t-1) = 1 \]  

(3.26)

with

\[ U_{at} = \overline{ett}_{a,t-1} + \overline{\varepsilon}_{at} \]  

(3.27)

\[ \overline{\varepsilon}_{at} = \sum_{k=1}^{t-1} w_k(t-1)\varepsilon_{ak} \]

Further as model I.

Model III
This model is as model II but only when a link was actually chosen can
information be acquired, so

\[ U_{at} = \begin{cases} U_{at0}, & \text{if } \sum_{k=1}^{t-1} \delta_{ak} = 0 \text{ or } t=1 \\ \frac{\sum_{k=1}^{t-1} \delta_{ak} w_{ak}(t-1)[\eta_{ak} + \epsilon_{ak}]}{\sum_{k=1}^{t-1} \delta_{ak} w_{ak}(t-1)}, & \text{otherwise} \end{cases} \] (3.29)

where \( U_{at} \) is the weighted average travel cost on link \( a \) at time \( t \), \( U_{at0} \) is the initial travel cost on link \( a \), and \( \delta_{ak} \) is 1 if the traveller has used link \( a \) in time period \( t \) and 0 otherwise.

The first two models are not very realistic. Model III however, is very promising, yet has to be developed further. The choice process assumes all travellers to be only utility maximizers. In Chapter 4 we will show that this view is too limited.

**Departure time choice**

De Palma (1992) gave a clear overview of research on the day-to-day departure time choice modelling. The path that will be discussed here does contain the concept of information. However, this is not further developed.

In order to model the dynamic departure time process, a state of the transport system must be defined. We will follow mainly the approach as presented by Ben-Akiva and de Palma (Ben-Akiva et al., 1984, 1986) Assume that the state of the system on day \( t \) depends on the previous days. In order to make matters not too complex, a first assumption of finite memory is made. This means that the state of the system on day \( t \) depends on the states of the previous \( M \) days. This relaxation is questionable. Only for matters of computational complexity can this assumption be allowed. From a behavioural point of view however there is no clear explanation for this finite memory.

Secondly, the problem is discretized by defining departure time intervals instead of the continuous time axis. The state of the system can be represented by an \( n \times 1 \)-vector \( X_t = [X_{1t}, \ldots, X_{nt}] \), \( X_{kt} \) representing the number of travellers who have selected alternative \( k \), i.e. departure time interval \( k \), on day \( t \). \( n \) is the total number of departure time intervals. So the state of the system corresponds to endogenous information, acquired by the various travellers on a given day. There is also exogenous information \( I_t \), not the outcome of any decision, e.g. weather conditions.

In a basic approach to the problem \( M \) is set to 1. On day \( t \) travellers base
their decision on \( X_t \) and on exogenous information \( I_t \). Let \( P_{k|j}[X_{t-1}, I_t] \) be the probability that an individual chooses alternative \( k \) on day \( t \), while he chose \( j \) on day \( t-1 \). So,

\[
P_{k|j}[X_{t-1}, I_t] = 1 - \sum_{j=1, j \neq k}^{n} P_{k|j}[X_{t-1}, I_t]
\]

(3.30)

Further

\[
X_k = \sum_{j=1}^{n} X_{j,t-1} P_{k|j}[X_{t-1}, I_t]
\]

(3.31)

Under the assumption that \( I_t = I \), using Brouwer's theorem it can be proved that a stationary solution to the above system of non-linear difference equations does exist, but, it has not been proved that the solution is unique.

A relatively simple specialization of the above model has been suggested by Ben-Akiva and De Palma (1986). Suppose that a choice may or may not be reviewed on any one day. This reviewing process has been modelled as a time-independent stochastic process \( \Omega_k \). Thus the probability becomes

\[
\Omega_k P_{k|j}[X_{t-1}, I_t] \quad \text{with } j \neq i
\]

(3.32)

Another simplification is that the alternative chosen on day \( t-1 \) does not influence the alternative chosen on day \( t \) when the individual is reviewing. Again this simplification is highly questionable, certainly from a behavioural point of view. In fact the model system is made less dynamic by this assumption. Only computational convenience seems to justify this simplification. So

\[
P_{k|j}[X_{t-1}, I_t] = P_k[X_{t-1}, I_t]
\]

(3.33)

The question remains what functional form must be used for the conditional probabilities. One way is to use a multinomial logit (e.g. McFadden, 1974). Then

\[
P_k[X_{t-1}, I_t] = \frac{\exp[-V_{k,t-1}/\sigma]}{\sum_{j=1}^{n} \exp[-V_{j,t-1}/\sigma]}
\]

(3.34)

The variable \( V_{k,t-1} \) represents the perceived cost to the individual of alternative \( k \) on day \( t-1 \). So it holds that

\[
X_k = [1 - \Omega_k] X_{k,t-1} + \Omega_k \sum_{j=1}^{n} \exp[-V_{k,t-1}/\sigma] X_{j,t-1}
\]

(3.35)

Conclusion

It is clear that difference equations like (3.35) are very hard to solve. They have been derived under a number of strict constraints as information is time
independent, the reviewing process is time independent and only related to the choice alternative and finite memory of individuals, which makes the model unrealistic. Also the fact that no learning process is defined makes this approach questionable. A solution can be derived if the reviewing process is independent of everything, which is not very realistic.

The formulation (3.35) however is promising in itself. When the goal of finding a solution is deleted this framework may be a way to proceed, but only if the strict assumptions under which it was derived are also deleted.

Still, with this in mind it may be interesting to look at a different, and in a sense more promising, approach as introduced by Mahmassani. This approach does not aim to find an equilibrium or steady-state solution. This approach will be explained further in Section 3.8.

3.8 A Micro-Simulation Approach

The area of research where the day-to-day evolution of route and departure time is studied using a simulation approach is almost entirely dominated by the work of Mahmassani. The background to this research is formed by a number of experiments that were performed to study the dynamic interaction between trip maker decisions and the resulting traffic system (Mahmassani and Herman, 1990). In these experiments real commuters were observed over several weeks. To study the decisions made by these commuters they were confronted with complete or limited information about the previous day. They had to make departure time decisions, and in some cases also route choices. The resulting travel times were determined by a computer simulated traffic system (Chang et al., 1985). Four different choice environments were created (Table 3.2).

<table>
<thead>
<tr>
<th>Choice environment</th>
<th>route choice</th>
<th>departure time choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>one route, limited info of previous day</td>
<td></td>
<td>*</td>
</tr>
<tr>
<td>one route, complete info of previous day</td>
<td></td>
<td>*</td>
</tr>
<tr>
<td>more routes, limited info of previous day</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>more routes, complete info of previous day</td>
<td>*</td>
<td>*</td>
</tr>
</tbody>
</table>

As a result of these experiments a model was developed. Key property of this model is a so-called switching module. This module is based on the concept of bounded rationality as originally proposed by Simon (1955). Bounded rational behaviour can be modelled by a simple satisficing decision
rule. This can be demonstrated by, for instance, focusing on departure time choice.

Let $D_{it}$ and $AT_{it}$ denote user $i$'s departure time and the resulting actual arrival time, respectively at day $t$. The acceptance of this outcome is based on introducing an indifference band $IB_i$. It is defined that an arrival time on day $t$ is acceptable if the binary variable $\delta_{it}$ is 1.

$$\delta_{it} = 1 \text{ if } |AT_{it} - DAT_{it}| \leq IB_i$$

$$\delta_{it} = 0 \text{ otherwise}$$

(3.36)

where $DAT_i$ is $i$'s desired arrival time, and $IB_i$ is $i$'s indifference band.

When $\delta_{it} = 1$, $D_{i,t+1}$ is determined by subtracting the anticipated travel time at day $t+1$, $ATT_{i,t+1}$, from the desired arrival time.

Now the anticipated travel time is defined as a function of all prior experiences with the system.

$$ATT_{i,t+1} = \sum_{t=t_0}^{t} w_t TT_{it}$$

(3.37)

Using (3.59) different learning strategies can be used to perform different sets of simulations.

Having defined the switching rules, the simulation model becomes complete by defining initial choices for route and departure time. This is done by applying a static stochastic user equilibrium assignment as defined in Section 3.5. The simulation approach is summarized in Figure 3.1.

---

**Figure 3.1 Overview of Mahmassani's approach**
3.9 Effects of Information: Capabilities of the Different Approaches

The next sections describe whether and how the different modelling approaches can be applied to determine the influence of information systems.

As was seen in Chapter 2 systems that provide information to road users provide prescriptive or descriptive information. The provision of information may either be individual or collective, and occurs at a point in time as well as space.

For example, in-car route guidance systems provide prescriptive information to drivers at certain points in time and space. A variable message sign can provide prescriptive as well as descriptive information at a certain point in time and space to all road users passing this point. Information from RDS-TMC (Radio Data System-Traffic Message Channel) can be both descriptive and prescriptive. Such information provision is collective and holds for a certain point in time and a range of points in space.

The main idea behind information provision is that road users do not possess perfect knowledge of the network, both in time and space. Therefore, deterministic approaches, which assume that individuals already have perfect knowledge, are by definition not suited to solve the problem.

Static models ignore temporal fluctuations by definition. This makes them not suitable to determine the effects of specific information systems.

To determine the effects of information an environment with and without information provision must be compared. The no-information environment may or may not be in a state of equilibrium. The information-environment is clearly in a non-equilibrium state. In terms of equilibrium: information is the incentive to push the system out of its disequilibrium state.

From the above observations it follows that in the next part of this chapter we will concentrate on dynamic, stochastic equilibrium and non-equilibrium models.

In the next sections all approaches will be discussed and it will be made clear why the dynamic stochastic day-to-day approach is the most suitable one.

3.10 Effects of Information: Static approaches

When information is regarded as a quality that solely reduces uncertainty irrespective of time and place, static stochastic approaches can be applied. Obviously in this manner specific information systems can be modelled.

Uncertainty is regarded as the variance of the error term in (3.6) that was used to model the perceived travel time. By decreasing this variance the reduction of uncertainty, i.e. the provision of information is mimicked.

This approach was first adopted by Koutsopoulos and Lotan (1989). They used a static stochastic user equilibrium (SSUE) approach and varied the
variance of the error term. This method takes into account the influence of uncertainty reduction on route choice only. Hamerslag and Van Berkum (1992) expanded this method by combining the SSUE and a spatial interaction model with elastic constraints into one simultaneous model to study also the impact of information on trip distribution and the spatial interaction of activities. They applied the method on different networks, and showed that the effect of information was highly sensitive to the lay-out of these networks, and to the level of congestion. The complete paper is in Appendix C.

3.11 Effects of Information: Deterministic Approaches

A deterministic approach is not suited to model the environment without information, because it assumes that road users are already perfectly informed.

This observation is not so trivial in the prescriptive case. Suppose we have defined a deterministic equilibrium. This means that no individual road user can improve his travel time by route diversion. Suppose further that a route guidance system is introduced. Each individual with the same origin and destination and departure time will get the same advice, also in a situation without incidents, or non-recurrent congestion. For each individual it holds that the advised route may either be the same as the original route, or different. Route diversion will not occur when demand is low. This is due to the fact that a guidance system is based on the all-or-nothing concept. In all other cases individuals will not benefit by following the advice, by definition. This clearly is not a realistic way of modelling. It would mean that when the effects of an information system are to be modelled, a stochastic approach must be followed.

This observation is supported also by the next example. Suppose a situation without information is modelled by a deterministic equilibrium. First an equilibrium must be determined without taking account of the incident. Then with the changed network (with the incident) another equilibrium is determined. By comparing the two, the effects of information is modelled, since the second equilibrium assumes that every user knows about the incident. Yet, with this approach it is not possible to distinguish different groups of road users, those with and those without information. Maybe more important is that all individuals are assumed to be perfectly informed, thus with information all drivers can predict and oversee the full consequences of the incident on the whole network.

We can conclude that a deterministic approach is not applicable to model the impact of information. If the assumptions underlying for instance a deterministic equilibrium were true, prescriptive information systems would only have negative individual effects, while descriptive information systems would be useless since all drivers already have perfect knowledge of the
network.

3.12 Effects of Information: Within-day Dynamic Approaches

As was seen in Section 3.6 the within-day dynamic, stochastic approach was initially proposed by Ben-Akiva, De Palma and Kanaroglou (1986). A sequential decision-making process was suggested, based on a random utility maximizing model. Together with a demand adjustment mechanism, a choice set definition and a travel time model a framework for general networks was developed by Vythoulkas (1990).

As was stated in Section 3.9 the equilibrium approach can only be adopted for situations without information. However, information as an abstract quality could be introduced in the model in the same manner as was done in the static stochastic approach. The variances of the different utilities used may become smaller, such that the parameters $\mu_t, \mu_r$ in (3.18) and (3.19) get different values.

When a specific system is introduced that provides descriptive information, the disaggregate approach cannot be used, unless instead of the logit formulations corresponding non-aggregate formulations are used. This means that individual expectations (including a learning mechanism) must explicitly be part of the model.

When prescriptive information is provided, a dynamic flow-oriented stochastic approach may be applicable. Since these information systems mainly focus on route choice, the departure time choice module may be deleted from the above procedure. Hence, input of the procedure is a dynamic OD-matrix, i.e. an OD-matrix with departure rates and volumes per entry. Stevens and Hounsell (1992) developed a stochastic version of CONTRAM, where the route choice process was made stochastic by adding error terms to the link travel times, using the nested choice structure as proposed by Ben-Akiva and Lerman (1985). Thus the joint probability for route and departure time choice becomes

$$P_{rt} = \frac{e^{n_r V_n}}{\sum_k e^{n_r V_n}} P_t$$  \hspace{1cm} (3.38)

where

- $V_{rt}$ the measured utility experienced by a driver departing at time $t$ using route $r$
- $\mu_r$ scale parameter associated with the route choice process
- $P_t$ the probability that an individual will depart at $t$
After the introduction of route guidance unguided travellers would follow a choice rule as denoted in (3.7) for their route choice, and guided travellers would follow the advised route. Since in situations without information no guided travellers exist, this assumption makes it possible to determine the effects of route guidance for any penetration rate.

Since Hamerslag's dynamic assignment method is better capable of dealing with large networks, and can easily be made stochastic, just as CONTRAM, this approach would be worthy of being followed.

However, all approaches in this context are basically aggregate. This means that, since individual behaviour is not modelled explicitly, no individual benefits from information can be determined.

3.13 Effects of Information: Day-to-Day Dynamic Approaches

The day-to-day dynamic approach, preferably conducted by microsimulation is best suited to integrate the concept of information.

Cascetta et al. (1992) introduced a doubly dynamic model. Both within-day and day-to-day dynamic properties are part of this model. However the concept of information is introduced solely as an abstract quality, that only influences the day-to-day dynamics part.

As was introduced by Ben-Akiva a certain, fixed fraction of the road users review their previous choices. Route and departure time choice are modelled by means of a nested logit model as in (3.18). Further he follows basically the work of Vythoulkas (1990). By defining the probabilities as logit models, with the associated variance parameters, information is modelled by reducing the variances.

The utilities used in the logit models stem from an obvious learning module as defined by (3.27). The new element in his approach compared to the one by Vythoulkas is the loading mechanism. Since the concept of information again is modelled inadequately we will not further discuss this method.

The simulation model proposed by Mahmassani is at present best suited to address the problem of information. In this model a switching module with the satisficing behaviour rule is adopted to model information. To do this, the current behaviour and information are compared. The concept of bounded rationality implies that information will alter current behaviour only when the advantage is bigger than a predefined indifference band.

For route choice this means for instance that route switching only occurs when the benefits of switching exceed a predefined minimum and a certain proportion of the remaining trip time (Mahmassani and Shen-Te Chen, 1992). Suppose the car driver is at a certain node in the network. A binary variable \( \delta_i \) is defined as:

where
\[ \delta_i = \begin{cases} 1 & \text{if } TTB_i - TTC_i > \max[\eta_i, TTC_i, \tau_i] \\ 0 & \text{otherwise} \end{cases} \] (3.39)

- \( TTB_i \): travel time on best path to destination (the best path and the travel time are provided by the information system)
- \( \eta_i \): relative indifference band for user \( i \), as a fraction of the remaining trip time on the current path to the destination: \( TTC_i \)
- \( \tau_i \): minimum improvement in the remaining trip time

So the information system provides \( TTB_i \) to road user \( i \). The same rule can be applied for the departure time choice.

Clearly, such an information system is not very realistic. However, this is the first approach where individual expectations are integrated in the model, and compared with the advice given. Therefore this approach is promising, and defines a way to proceed, but only if information is modelled more realistically and the choice process involves more than a single switching rule.

### 3.14 Discussion

From all the assignment methods discussed only dynamic models are usable for our purpose. As seen in Section 3.11 static models cannot address the dimension time. For specific information systems, both time and place are important. Therefore, static models can only be applied to determine effects of information when information is defined as some abstract quality. This was shown in Section 3.11.

Deterministic models solve an equilibrium. Situations without information can be modelled as an equilibrium by these models, but these models cannot be used for our purpose because they assume that travellers have complete and perfect knowledge. This means that dynamic deterministic models are mainly of interest from a mathematical point of view. The applicability of these models is very limited.

Stochastic models could however be used to represent the situation without information. A within-day dynamic stochastic equilibrium that takes into account route choice explicitly is difficult to solve. It was shown that these models can usually be described by a set of difference-equations that are only solvable under strict assumptions. And even when they are solvable, it is usually very hard to find the solution.

In dynamics the distinction between day-to-day dynamics and within-day dynamics is made. For day-to-day dynamics the main assumption is that behaviour today can be derived from behaviour in the past. This involves a learning process, that is usually modelled by a filter on the travel times of routes. After a sufficiently large number of iterations a stable situation usually
occurs, but not necessarily an equilibrium.

Within day dynamics involve the temporal evolution of traffic flows over a certain period, e.g. a day. In the solution an iterative procedure often is applied, comparable to the iterations in the solution method for the static deterministic user equilibrium. It can be argued that this process and the learning filter are, in principle, the same. Both methods use data from the past (past in time, or past in iterations) to calculate a new situation. Yet, these two methods are fundamentally different. This can be explained as follows.

Consider the first iteration of the solution-procedure to solve a static deterministic equilibrium. The first step is an AON-assignment. This could be translated by letting everybody choose the shortest route, when all travellers have complete knowledge of the network. In the next iteration a new AON-assignment is made with updated travel times, and a combination of the two is made. So for each OD-pair one or two routes are used at this stage. The 'chose best (or any) combination step' would have to be translated into a learning process. For a learning process this would imply that some people learn from experience and others not, or that individuals in the learning process would anticipate how other individuals respond to their previous experience. This is obviously not the case since they would need complete knowledge of all implications of the choices and behaviours of all other individuals. Thus when the flow update process is regarded as a learning model, this means omniscience for all drivers. This is similar to the learning Model I used by Horowitz (1984). Clearly this was the least realistic model.

In effect a learning process is a filter for variables that rule the process, like travel times. In the iteration procedure the update process is a filter for the resulting variables, such as the flows. Further, a maximum of one extra route can be chosen in one iteration between any OD-pair. Clearly in a real environment this cannot be the case. Therefore, iteration and learning are not the same and must not be confused.

However, it can be argued that even though the two modules are not the same, they yield the same solution in terms of flow patterns. But in the flow update module, route choice is not a unique way to yield the solution. This means that individual route choice behaviour cannot be derived from this. So, to determine individual benefits from information this approach cannot be followed.

In a stochastic model error terms are added, e.g. to travel times on links. This can be justified by stating that nobody is really certain of travel times, e.g. because people do not know specific links so well. The notion how well somebody knows an alternative, however, implies a history of choices and therefore dynamics. Thus, defining a static stochastic model is a *contradictio in terminis*.

In Sections 3.10 to 3.13 four different approaches to assignment were considered as the basis for evaluating information. One case dealt with
information as a specific information system, two considered information as an abstract quality that reduces the variance of travel times, one considered a dynamic route guidance system. It became clear that static approaches are too limited by definition.

The dynamic stochastic assignment by the updated version of CONTRAM can be used to define a no-information environment, but can only be used to evaluate route guidance, or other types of prescriptive information systems. It is not possible to integrate descriptive information, since the approach does not deal with day-to-day dynamics and therefore does not include a learning process, nor individual expectations. The within-day approach is used to establish a temporal flow pattern as a before-situation. Necessarily compliance with the advice must be set to a fixed percentage, since this approach cannot deal with behavioural considerations that deal with compliance.

The other example of modelling information was discussed in Section 3.13. Cascetta built a promising framework, but failed to model a specific information system. Mahmassani introduced complete information at a node. This specific information system is not very realistic, both from a behavioural and a technical point of view. The behavioural background is that at any node in the network the user must be assumed to have a clear notion of the remaining travel time to reach the destination. Further an information system must be introduced that keeps track of all users and thereby is capable of calculating all remaining travel times for all destinations. If the information system is to give these travel times at each intersection as was done in the computer experiments, this involves first heavy computation but for the user also heavy information processing.

In its present form this concept is not suited to deal with different sorts of descriptive information. However, it allows modification by a specific information-processing module.

In its present form the system is not suited to address prescriptive information systems in a different way to that by Stevens and Hounsell (1992)

Another notion can be put forward concerning an individual versus an aggregate approach. Suppose there are two individuals \( i_1 \) and \( i_2 \). Suppose further that there exist two choice alternatives \( a_1 \) and \( a_2 \). Suppose that \( i_1 \) chooses \( a_1 \) and \( i_2 \) chooses \( a_2 \). Due to the fact that both individuals are ill-informed this is not the best choice for either, although they think they are making the best choice. This situation could be modelled by a stochastic equilibrium. Now after provision of information both individuals make the best choice, i.e. \( i_1 \) chooses \( a_2 \) and \( i_2 \) chooses \( a_1 \). Although there exist by definition individual benefits on an aggregate level no effect can be measured since in both situation, with and without information both alternatives are chosen once. When the impact of information must be determined it is therefore necessary to use a disaggregate approach.
4

Dynamic Decision Making
in Travel Behaviour

4.1 Introduction

In Chapter 2 we stated that the user is the most complicated element of the triad information system - traffic system - user. It was also stated that the sum of the behaviours of individual users in the network makes up the traffic system. In this chapter we will try to arrive at a better understanding of the behaviours of individual drivers in this context, i.e. the way in which they choose between different alternatives. To do so this chapter will present an overview of the concepts of behavioural decision making theory that we feel are relevant to this thesis. The aim of a better understanding of individual choice behaviours is to establish what research findings can be used to specify the proposed model. It may be that current theory does not offer sufficient findings which are applicable to the proposed model. In that case, plausible and testable assumptions for the model must and will be made.

First, some preliminary theoretical notions about the way in which decision making is related to route and departure time choice will be discussed. In later sections of the chapter these notions will be discussed in more detail.

Models of travel behaviour are necessarily based on implicit or explicit assumptions about human decision making behaviour, particularly decision rules and knowledge states of decision makers. Traditional transport models (e.g. Hamerslag, 1972; Wilson, 1974) often assume that travellers are only utility optimizers. This means that they will continually search for and select alternatives with the best (expected) utility. Also, travellers are assumed to be constantly more or less perfectly informed about the state of the complete network. Not only do traditional models assume that travellers are only utility optimizers, they also operate from a single, compensatory decision rule, in which any bad attribute of a choice alternative is compensated by a good one. These assumptions are not necessarily behaviourally valid. Yet, these models have been used as
decision making tools for policy makers during the last decades. Of course, this does not provide sufficient evidence that the outcomes of these models are valid. Most modellers in the field of transport would admit that models of existing situations invariably require quite some calibration to arrive at plausible results.

The development of new types of information systems as discussed in Chapter 2 has made reconsideration of these assumptions necessary. Any modelling effort in this context needs to deal with externally provided information and particularly address the question how travellers respond to such information. This also makes it necessary to become more specific about the way in which travellers deal with 'internal' information, i.e. knowledge about the network and expectations about travel times. Since travel behaviours are carried out repeatedly, assumptions must be made about the way in which knowledge and expectations change over time. The ways in which these changes occur must be specified within the model. Because of the non-deterministic properties of the traffic system, and the experiences that follow from these, knowledge and ensuing expectations will most likely incorporate stochastic elements.

We all, at some time, make trade-offs to choose between different alternatives. However, many (and maybe most) of our choices are made without much mental effort and seem to result from habits. Although the relevance and strength of habit within behaviour has been recognized (James, 1890; Luchins & Luchins, 1950; Shiffrin, 1988), most models dealing with travel behaviour have thus far not explicitly formulated or integrated notions of habit. Ignoring habit seems not only behaviourally unrealistic, it might also lead to overestimation of the effects of new information systems. E.g. most models would assume that, when drivers are provided with accurate information about travel times, they would use this information to choose the time-shortest route. If habit plays a role in route choice, drivers may ignore information and choose their habitual route. Thus, it seems essential to us to take stability in choice behaviour and resistance to change as part of human behaviour into account. Later in this chapter we will provide a definition of habit.

To formulate a model that deals with individual travel behaviour which may be influenced by information systems, it is necessary to be specific about assumptions on the underlying decision-making processes. If such a model is also to serve as a framework for future research on decision making in travel, these assumptions should at least be behaviourally plausible. However necessary, it is not the aim of this thesis to validate the behavioural assumptions as a psychological theory. What we do aim for is the development of a theoretical and modelling framework in which the interplay of the traveller’s knowledge and uncertainty about options and outcomes, learning from experience, habitual behaviour and responses to externally provided information is described. It is important to do this because one can no longer postulate that all travellers
are more or less perfectly informed about their decision environment and that they are always "optimal" decision makers.

The outline of the remainder of this chapter is as follows. In Section 4.2 we will address the nature of the dynamic decision processes involved. Section 4.3 deals with learning, knowledge and experience as constituents of the dynamic decision process, while Section 4.4 deals with the concepts information and uncertainty. In 4.5 the main attributes on which route choice decisions are based are discussed. Section 4.6 presents a brief overview of decision rules. Section 4.7 presents some views on variability in travel behaviour and the meaning and function of habitual behaviour. Section 4.8 again focuses on information, this time in the context of user responses to travel information systems.

4.2 Decisions and Dynamics

Central to behavioural theory on decision making are the concepts decision, judgment and choice. These terms are not always precisely defined and, consequently, are sometimes used interchangeably. Semantically and phenomenologically it seems that choice is more action-oriented and judgment contemplation-oriented. According to Karlsson (1988) choice is experienced as a situational demand to select a fixed alternative, while decisions involve a more creative act. Judgement on the other hand requires explicit evaluation of each alternative, typically using a continuous or multi-level scale (Billings & Sherer, 1988). The distinction between choice and decision seems less germane than the difference between choice (and decision) and judgment. In line with tradition in decision making research (e.g. Einhorn & Hogarth, 1981; Rapoport & Wallsten, 1972; Slovic, Fishhoff & Lichtenstein, 1977) we will use decision to encompass choice, and will indeed use both terms as interchangeable. However, it is important to distinguish choice from judgment, since results from research using judgment responses should not be generalized to choice tasks. A study by Billings and Sherer (1988) for example, indicates that choice tasks lead to less search for information, less interdimensional search for information, and less variability of information searched across alternatives then do judgment tasks. It seems that choice tasks lead to less complex cognitive processing than judgement tasks. We will assume the route and departure time choice task to be a choice task and not a judgment task. Fortunately, this allows us to keep the complexity of cognitive processing at a fairly simple level.

We assume the choice behaviour of decision makers to be intelligible and goal directed. This implies that by making a choice the decision maker aims to achieve some goal, for instance arriving at a destination at a preferred time. Although we may have some ideas about the distribution of different goals within a travelling population, we cannot hope to be aware of all personal goals. Therefore a model which describes individual travel choice behaviours cannot
take the diversity of personal goals into account in the sense that these goals are an explicit input to the model. Instead, by introducing stochastic terms into the model, we do allow for disparate objectives for different decision makers (Baron, 1988). Such terms also allow decision makers to be only partially informed about existing alternatives and the 'true' attributes of perceived options.

Furthermore, we postulate that decision makers do not necessarily optimize, and in fact may skip optimizing altogether. This implies that we cannot adopt a strict normative approach in which decision makers will always select the best alternatives according to the available information (Von Winterfeldt & Edwards, 1986). In fact, decision makers may select alternatives merely on a habitual basis. We will return to these assumptions in later sections.

At this point the most relevant assumptions which have shaped our ideas about route choice and timing decisions have been presented briefly. We will now focus on the properties of the choice problem at hand.

On a descriptive level, the complex problem the decision maker faces is quite simple. Assuming that drivers have already decided to travel from A to B, they must now only decide when to leave and what route to take. Simple as this may seem, this is what Newell and Simon (1972) described as an ill-defined choice problem, because (a) the complete choice set is not known to the decision makers - in fact for the same choice problem, the perceived choice set may vary from one decision maker to another - (b) the relevant outcomes of all choice alternatives are not known to decision makers, and cannot be known because these are partly determined by unknown externalities, such as behaviours of other decision makers, the weather, etc. (c) the probabilities of anticipated consequences are not fully known to decision makers. Most assignment models seem to have failed to grasp the impact of these observations, because they adhere to the assumptions of the normative approach, which was designed for fully defined choice problems and presume decision makers at any time to be perfectly informed about the complete choice set and the consequences of each choice. This also relies on the decision maker's ability to quantify both probabilities and utilities of consequences (Vlek & Wagenaar, 1976). The fact that route and timing decisions are ill-defined choice problems implies that trade-offs between alternatives can result in inefficient choice behaviour since drivers are not fully informed. Any realistic conceptualization of the trade-offs drivers make should at least be based on plausible ideas about what information, i.e. knowledge and expectations drivers actually have available at a certain time.

Route and timing decisions must be conceived as mutually dependent. In many cases, the choice when to depart from A will be related to the preferred arrival time at B. The travel time between two points in a network may depend on the departure time choice and will almost certainly depend on the route choice. It is clear that one cannot solve a route and timing problem in a network that is fully unknown, unless time and money constraints are absent. E.g. if a driver
is asked to deliver a parcel in Vorchten, he would probably first require some information on the location of this hamlet (see also opening citation). So normally, to make a decision, at least some information on the distance between the origin and destination and preferably on the expected travel time along some route between these two points would be necessary. A model must define in some way what these initial knowledge and expectations are assumed to be. Thus far this initial values problem has received limited attention in choice modelling.

We have not yet addressed one fundamental property of route and departure time choice behaviour, namely its dynamic nature. Some trips are made repeatedly between the same origin and destination (O-D), and the circumstances under which these trips are made vary over time. This implies that the choice behaviours underlying travel must be described as dynamic. In Rapoport's words, 'decisions are made sequentially in time, the task specifications may change over time, either independently or as a result of previous decisions; information available may be contingent on the outcomes of earlier decisions; and implications of any decision may reach into the future' (Rapoport, 1975, p. 349). Dynamic decision making seems a somewhat neglected area in research on behavioural decision making. The reasons for this are probably the complexity of dynamic decision processes and the fact that researchers have only partly succeeded in developing tasks to study such behaviour in controlled experiments (Rapoport & Wällsten, 1972). Most published research in this area has been done on human control in optimizing tasks within a dynamic programming model (Rapoport, 1966). In this model the task of decision makers is to make decisions at the beginning of discrete time stages. At the beginning of stage \( t_k \) the subject obtains information about the present state of the environment in which he is operating and makes a decision, \( c_k \). The changes in the environment during stage \( t_k \), and the resulting state of the environment at the beginning of stage \( t_{k+1} \) depend on the state of the environment at \( t_k \), upon \( c_k \), upon a random variable \( e_k \) having a probability distribution which is known to the subject, and upon \( n - k \), where \( n \) denotes the total number of decisions to be made. Though this process may resemble choice behaviour in transport, important differences obviously exist. The main difference lies in the fact that the random variable \( e_k \) in the transport environment has properties which are not (immediately) known to the decision maker because these result from - among other things - the choice behaviours of other travellers in the system. Because, in research carried out within the frame of the dynamic programming model, decision makers are often presented with fully defined choice problems (Newell & Simon, 1972), results have limited relevance to our endeavour. Concerning the methodology for research on dynamic decision making, Kleitner (1975) has already indicated that simulation of such behaviours might be the better way to proceed, because dynamic decision making is too complex to study experimentally. Although we agree with Kleitner's pragmatic argument, the possibilities to validate simulation models from a
behaviour theoretical point of view are limited. Still, it is necessary to adhere
to a dynamic definition of the choice behaviours we are dealing with. First
of all, momentary individual expertise on expected traffic conditions is clearly
a result of experience from outcomes of previous choices. Of course, diffusion
of information within the travelling population, for instance by word-of-mouth
or media reports, also influences momentary individual expertise (Lerman &
Manski, 1982). New information systems will now add to information diffusion
and more instantaneously to individual expertise.

4.3 Knowledge, Experience and Learning

Dynamic decision making deals with decisions that are made over time.
Furthermore, future decisions may be contingent on the outcome of previous
choices. Therefore it is necessary to be specific about the feedback mechanisms
which may be involved. On the individual level this feedback may be described
as a learning process, which means that the decision maker acquires knowledge
and forms expectations about the environment in which decisions are made.
To preserve this knowledge a memory must be available and, moreover, a
mechanism which deals with modifications to this memory’s contents. Since
decision makers deal with an evolving decision environment, the underlying
modification mechanism cannot be defined as an all-or-none learning process,
but must be understood as a successive adaptation of knowledge which is based
on the outcomes of previous decisions. There does exist some research on this
subject, namely probability learning or probability matching (Estes, 1988;
Klayman, 1984). The task of decision makers in this line of research is to learn
about deterministic or stochastic properties of a sequential learning task. This
research supports the following conclusions: (a) the process of learning comprises
a population of aspects or cues that are randomly sampled from trial to trial;
(b) contextual elements sampled on a trial become associated with the event
that occurs; (c) judged relative frequencies or probabilities of two events are
in the ratio of the proportions of contextual elements associated with them in
memory. Furthermore, most of the time the formation of long-term memory
representations seems to be the basis for responses relating to event frequency
or probability (Estes, 1988). The probability learning paradigm is not completely
usable in this context, because the experimental tasks which are mostly used
in this line of research adopt a normative approach. That is, there is some
predefined optimal solution to the task at hand, so that once subjects have grasped
the fundamental regularity leading to certain outcomes, they can perform
optimally. Therefore, in the end, the task resembles an all-or-none learning
task. The traffic system does not possess such a regularity, since the stochastic
properties of the decision task are in large part due to decisions made by other
travellers and other exogenous factors. Nevertheless, this does not mean that people necessarily perceive the traffic system as totally unpredictable.

Though we will later describe what attributes drivers may use to select a route, we will already generally state the following about knowledge and expectations. The contents of the knowledge decision makers have, which is relevant to the choice task at hand, must in some way be linked to the most predictable dynamics within the transport system. Although this does not mean that decision makers have the ability to predict these dynamics per se, their knowledge states should allow for a certain awareness of these dynamics. To be more specific, decision makers may be aware of time-dependent fluctuations within the traffic system. For instance, they may experience that during peak hours travel times are likely to be longer than during off-peak hours. The fact that travellers can be aware of such fluctuations must be represented in their expectations. We are not aware of any research which has investigated in what way decision makers may categorize knowledge into different registers, nor how many registers might be used by them.

Also, decision makers must be able to be aware of exogenous information sources: if they hear on the radio that their usual route from home to work is congested, they may search for alternative routes. This implies that a direct link between the knowledge structure and exogenous information must be assumed.

As stated before, we can no longer assume travellers to be perfectly informed about the state of the network they are travelling in at all times. A further fundamental question is whether all options are available to all travellers. If such were the case, it would mean that although travellers do not necessarily know about all attributes of links in the network, they do have complete knowledge about the structure of the network, i.e. the existence of all links. Previous work has shown that this is not the case. For instance, Bovy & Stern (1990) report that cyclists considered at the most four to five routes from a set of forty real alternatives. It seems unlikely that this finding will be very different for car drivers. So, in any more complicated network a large number of possible routes between OD-pairs may exist, but only a few will be known to each individual. Of course, experience and exogenous information may lead to expansion of this knowledge.

Concluding, to formulate a procedure which describes learning from sequential decisions in a transport environment, the following must be specified:

1. the attributes of knowledge and expectations
2. the initial knowledge and expectations at $t_i$, that is, when the first decision is made
3. a link between experiences, external information, knowledge and expectations
4. the knowledge adaptation process(es) involved
5. the time span of memory, i.e. how long are experiences available to the decision maker
We will return to these points in Chapters 5 and 6.

4.4 Information and Uncertainty

In the previous sections the terms knowledge, expectations and information, were used without proper discussion. In this section we will discuss these terms in some detail.

Knowledge refers to what drivers know for certain. For instance, a driver knows a route between A and B exists or he does not. The counterpart of knowledge is ignorance. Contrary to knowledge and ignorance, expectations imply a degree of uncertainty. E.g. drivers expect that their trip from A to B will take no more than 10 minutes, but they cannot be certain that this will actually be true. Information can either expand or correct knowledge, or update expectations, or reduce uncertainty.

In Chapter 2 it became clear that information in this context is a concept which is hard to define, because what information is depends both on the characteristics of the users, particularly their present knowledge state and expectations, and on the reason why the information is needed. For example, a delay message may have a different meaning for a business man trying to make it to an appointment on time, than for a recreational traveller on a leisure trip. Also, a city-map provides different types (and amounts) of information to a tourist, a historian and a planner. Therefore the "same" information need not reduce the ignorance and uncertainty of different travellers to the same extent, even if identical initial knowledge levels and expectations are assumed.

There is no commonly agreed quantitative measure to assess amounts of information which is applicable to all problems dealing with information. One, in our eyes usable, view links the amount of information with the statistical concept of variance (Norman, 1976). Variance can always be stated in terms of the unit of measurement, be it time, distance, costs or whatever. The similarity of variance and the amount of information might be explained as follows: when there is large variance in possible outcomes, decision makers are very uncertain about what is going to happen. If the variance is very small, decision makers are fairly sure about what is going to happen. At the same time the concept of variance can be used as a measure of uncertainty.

Uncertainty is related to the concept of risk. Several authors have formulated measures of risk. For example Weber (1988) suggested conjoint expected risk (CER) to predict a person's subjective risk judgment for risky choice alternatives. Weber claims CER is superior to the risk concept proposed by Pollatsek & Tversky (1970). Unfortunately, CER is calculated from seven parameters (probabilities for breaking even, negative outcomes and positive outcomes,
and two variants of conditional expectations about non-zero outcomes). Pollatsek & Tversky’s risk concept had only two, namely the expected value and the variance of the choice problem. Weber’s CER measure could on average account for 69% of the variance in risk judgment in gambles, while Pollatsek & Tversky’s could still account for 59% of this variance. Although these studies are based on the traditional multiple betting-games line of research, which assumes independence of chances, the simplicity of Pollatsek & Tversky’s risk concept has appeal for our modelling framework.

It is assumed that the tendency to choose any option is a function of the perceived likelihood and attractiveness of alternative consequences. The likelihood of consequences or the uncertainty of travel alternatives depends on the knowledge state of the decision makers and the external processes which generate this uncertainty (Howell & Burnett, 1978; Kahneman & Tversky, 1982). How people deal with decision making under uncertainty is conceptualized thus far either in cognitive heuristic frameworks (Kahneman, Slovic & Tversky, 1982) or in 'imperfect' normative approaches (Manski, 1977; Simon, 1955), or mixes of both.

How people deal with uncertainty depends on a complex of factors such as problem context, complexity, task setting, span of events and response task required. E.g. it has been shown that people have risk-seeking preferences when confronted with possible losses and show cautious behaviour when they must choose between possible gains. (Kahneman & Tversky, 1979; Van Schie, 1991).

Another example is that people make different judgments when the task is to estimate the frequency of an occurrence, than when the task is to estimate the probability of an occurrence, or to predict the outcome (Howell & Burnett, 1978) Although these considerations are certainly relevant from a theoretical point of view, they seem too specific to be of consequence to our modelling effort.

In this section we have tried to clarify the distinction between a number of concepts that seem relevant to decision making. It can be concluded that the need for information is either a consequence of ignorance or uncertainty. It seems possible to link the concept of variance to both information and uncertainty. Furthermore, except for the previous conclusions, it seems that many research findings on how people deal with uncertainty are too specific for our modelling purpose.

4.5 Knowledge Attributes

In the previous section the general concept of knowledge and related terms were discussed. In this sections some literature on the contents of knowledge,
that is, the attributes of choice alternatives which are relevant to driver choices, will be discussed.

Some attributes of alternatives are highly stable, e.g. mode comfort for cars (but cars can also break down or get involved in accidents). Other attributes have a more stochastic nature, e.g. travel times.

Within transport modelling it is generally assumed that travel time is one of the major criteria drivers use to choose a route. Empirical studies on this subject do not always confirm this assumption at first sight. For instance, Janssen (1985) investigated route planning of 1,661 car drivers and found that shortest travel time had been the major reason to select a certain route in only 27% of recently made trips. Janssen found that familiarity with the route (14%), shortest distance (9%), beauty (8%), absence of congestion and safety (both 7%) and absence of intersections (6%) also contributed significantly as route choice criteria. The remainder of criteria that were mentioned by drivers were: traffic density, road conditions, signposting, and suitability for easy driving. Of course, the other criteria are not necessarily contradictory to the shortest time criterion. In fact, other studies confirm that shortest time is the most important criterion. For instance, Duffel & Kolombaris (1988) found that 54% of car drivers who were familiar with a certain area responded that shortest time had been the major reason for their route choice. However, in practice 91% did actually drive the time shortest route. In another study, Wootton and Ness (1989) reported that 70% of the drivers try to drive the time shortest route, though only about 50% seem to succeed in achieving this goal.

It would be easy to extend this list of studies and also to provide more - and sometimes contradictory - percentages on the most important route choice criteria (see also Bovy & Stern, 1990). However, we choose not to do so, but to conclude that travel time will be at least one important route choice criterion. Furthermore, in accordance with what was said about uncertainty in Section 4.4 it seems that experienced variance in travel time may capture sensitivity to criteria such as congestion and 'intersections'. For modelling purposes it will not be possible to include an exhaustive list of route attributes. Dependent on network and the information provided by information systems, it must be decided whether additional choice attributes are necessary.

### 4.6 Decision Rules

Modelling decision-making can be approached from three different angles: descriptive, normative or prescriptive. Descriptive models are about how people normally think, decide and act. Normative models are concerned with how people ought to decide and act. Often a basic assumption in the latter models is that of homo economicus. Research shows that these models often lead to results which indicate that we violate principles of proper thinking ourselves,
that is, that we are biased (Kahneman et al., 1982). The third angle is formed by prescriptive models. These state one distinct, best way in which we should decide or act. Many expert systems are good examples of such models. The aim of these models is not to simulate actual behaviour but only a best behaviour.

From a theoretical perspective a descriptive approach would be a good basis to start from. For the purpose of this thesis a major disadvantage is the fact that hardly any comprehensive, descriptive models have been developed yet. When it comes to modelling of behaviour, more normative approaches become inevitable.

Normative models are often based on the utility maximizing assumption. The classical utility concept is essentially concerned with inference and not with search. Models based on this classical concept assume that, when we choose, we already have before us all our possible choices, our goals and all the evidence we need: we do not need to search for any of these. Classical utility theory therefore provides at best only part of a usable theory of decision-making. The rest of the standard has to do with search for alternative actions, goals, evidence about the consequences and their probabilities. The theory of probability provides an additional normative standard, which tells us how probabilities of consequences should be calculated.

Utility as a concept represents anything that people want to achieve. Although in many cases utility has been translated as monetary value, all kinds of subjective values and desirabilities are in fact utilities. The normative character of utility theory lies in the fact that it describes how we should measure and maximize utility. It seems possible to deal with uncertainty as a utility component per se. The risk measure proposed by Pollatse & Tversky (1970) might be construed as a disutility assessment in which uncertainty (variance) is an explicit component.

It is clear that in travel behaviour both individual utilities and uncertainties are hard to determine. We cannot assume that all travellers will evaluate the same alternatives in terms of equal utilities. For instance, some people will value travel times most, others distance and still others may be searching for the most scenic routes. Even if different people were to associate the same utilities to different options, they could still differ on their estimation of the probability of outcomes. For example, if two people were to choose between two routes and they both wanted to take the fastest one, their appraisal of the likelihood that one of the routes was in fact the fastest need not be the same.

Normative theories of choice behaviour are only partially correct as descriptions of real-life human choice behaviour. Many experiments show we violate principles of normative choice. The violations may be understood as a result of the use of misleading heuristics, which are a consequence of the way in which we react to risk, that is uncertainties that could have a large effect on the outcome of an option. However important this finding may be, normative theory does offer at least one convenient and usable decision rule to model decision making.
Nevertheless, normative theory is incomplete, so other choice rules must also be incorporated in the model. We will return to this later.

Once a person has experienced certain travel options, the properties of the probability-utility curve can be determined by actual experienced utilities or by external information. When a choice is made for the first time however, the individual has no experience. Therefore, it is necessary to assume that people have initial expectations about fundamental features of different route and timing options. How people arrive at these expectations is not immediately clear. E.g., the expected travel time for a route one has never driven before may be 'extrapolated' from the cognitive map of the network, i.e. distance perceptions, or may be obtained from other travellers. Once people have driven certain routes their initial expectations for following choices can be based on actual experience.

It is generally assumed that, in order to make a choice, decision maker may apply one or more decision rules to a set of choice alternatives. We have already mentioned the normative, utility maximizing approach to decision making. The question remains what other rule(s) or heuristic(s) drivers use to select alternatives. This question is important since a model about route and departure time choice has to be based on a procedure which mimics such rules.

Literature on the subject shows a wide range of different rules which might or might not apply to certain choice problems (see Svenson (1979) for an overview). Although it is important that a decision rule is behaviourally plausible, it is also important that such a rule is applicable in a model, i.e. the rule must be computationally convenient and not impose too heavy demands on data collection.

It can be concluded that a descriptive theory on decision making of route and timing choice tasks is not yet available. Lacking a useful alternative, we are forced to use standard normative theory. Because we need to incorporate individual differences in the expected utility of different options, subjective or random utility theory (e.g. Manski, 1977) seems to offer a usable model for one of the necessary decision rules within the model. One of the drawbacks of random utility theory is that it implies continuous, complex mental processing. We agree that one of the (implicit) personal goals of most people is to minimize the time they spend on thinking and making decisions (James, 1890; Janis & Mann, 1977). It seems that performance of habitual behaviour is one of the ways to achieve this. In the next section we will elaborate on habit and its counterpart, variability.

4.7 Variability and Habit

The importance of variability in travel behaviour has clearly been recognized (e.g. Jones & Clark, 1988; Huff & Hanson, 1986). Much of this interest stemmed from methodological questions, which arose from the idea that the type of data
obtained, and especially the period over which data are obtained, has great importance for the possibility to draw valid conclusions about the nature of travel behaviour. Many transport studies are based on one-day travel diaries and implicitly are based on the assumption that individual travel behaviour is highly stable. Studies which explicitly address this issue are concerned with day-to-day variability in travel behaviour and point out the necessity to gather data over a period of many days (Hanson & Huff, 1988; Huff & Hanson, 1990).

Definitional and measurement problems concerning variability and the types of behaviour it pertains to have been addressed by a number of authors, though never completely satisfactory (Huff & Hanson, 1986, 1990; Hanson and Huff, 1988, Jones and Clarke, 1988). The fact that travel behaviour is such a complex issue concerning locational, activity, route, mode and timing decisions, which all may be contingent on trip-chaining considerations, makes investigations into the variability of travel behaviour as a whole at present impossible. Most studies therefore focus on certain aspects of travel behaviour, like the number of stops for different activities (Huff & Hanson, 1990), activity patterns (Jones & Clark, 1988), departure time choice (Manning, 1989; Hatcher & Mahmassani, 1992), and route choice (e.g. Mahmassani & Herman, 1990; Hatcher & Mahmassani, 1992).

Though quite some research has addressed variability in travel behaviour, fewer publications have addressed the role of habit in this context (see Rooijers & Steg (1991) for an overview). Probably one of the first psychological accounts on the subject was by William James (1890). James’ naturalistic and moralistic ideas on habit were developed along the lines of the properties of physical materials. He states his view on habit as follows: ‘the phenomena of habit in living beings are due to the plasticity of the organic materials of which their bodies are composed’. On a functional level he asserts: ‘habit diminishes the conscious attention with which our acts are performed’, which allows for more attention to go to more important tasks. James even makes it his credo to ‘make automatic and habitual, as early as possible, as many useful actions as we can’.

Within the psychological literature James’ ideas on habit have been extended to the field of attention (e.g. Shiffrin, 1988), in which what James called habit is predominantly viewed as a learning process, and differentiated into skills, automatic processing, and sets. Choice which is based on habit should not be confused with skill. Car control, the combination of perceptual and motor behaviours which are required for driving a car, may indeed be conceived as a skill, a set of automated behaviours. In fact, car driving can only be performed adequately once these behaviours are automated (see also Hale, Quist & Stoop, 1988).

A second psychological field that deals with the phenomenon James termed habit is human error (e.g. Hale & Glendon, 1987; Hale, Stoop & Hommels, 1990; Rasmussen, Duncan & Leplat, 1987; Reason, 1990). Rasmussen distinguished three levels in human performance: skill-based, rule-based, and
knowledge-based. Skill-based performance is governed by stored patterns of preprogrammed instructions and is applicable to routine tasks. The rule-based level is applicable to tackle familiar problems in which solutions are stored by rules of the if-then type. The knowledge-based level applies to novel situations for which actions must be planned on-line using conscious analytical processes and stored knowledge. It seems that route and timing decisions are rule-based or knowledge-based depending on the novelty of the situation. It seems that the proposed model should take both levels of performance into account.

It is suggested that people generally try to avoid making trade-offs (Janis & Mann, 1977). One way to avoid trade-offs is by automating choice, which means that the intentional cognitive process leading to the choice is skipped. We state that habit can be seen just as that.

Before we try to give a definition of habit which is suitable for the specific behaviours we are concerned with, we will comment on two related terms, 'hysteresis' and 'inertia', which are also frequently used. In transport, habit, hysteresis and inertia are more often than not used as synonyms (Banister, 1978; Blase, 1979; Goodwin, 1977). Most of these studies depart from a specific definition of habit (though not always explicitly). For instance, Goodwin (1977) defines habit as 'various sources of resistance to change that on purely economic grounds would be made'. From this, it seems necessary to introduce some change to establish whether a certain behaviour is influenced by habit. This also holds for hysteresis, which is defined by Blase (1979) as 'the delay present when there is not an immediate response by an affected variable due to the influence of a causal variable'. Inertia, in general, may be defined as the property to persist in a certain state.

In our view, habitual behaviour is not necessarily preceded by change or a changing force. Nor should such a change be present to be able to measure the existence of habit. Thus it is important to recognize the existence of habit in stable environments. We therefore define habit simply as the propensity to repeat certain behaviours. The term intentional here connotes to a rational trade-off between available and perceived alternatives, implying utility considerations of the alternatives. Some researchers (see e.g. Svenson, 1979) have implied that habit may be seen as a simple heuristic, 'just do what you have done before'. This idea may be supported by results from protocol analyses of mostly consumer choices, but we feel that the interpretation is not completely valid, because it still implies a conscious or intentional process (cf. Nisbett & Wilson, 1977).

Conclusions
In this chapter we have defined route and departure time choice as dynamic decision making behaviour. This definition implies that drivers learn from their experience. For our modelling purpose this implies that the contents of knowledge must be specified, and also a process that describes the way in which people learn. We elaborated on the criteria drivers use for route choice and on the
meaning of uncertainty. We found that travel time will probably be one of the most important criteria drivers use to choose a route. We also found that it seems possible to use variance to represent uncertainty, e.g. in travel time.

It became clear that a descriptive theory of decision making, that can be used for our purpose, does not yet exist. We concluded that normative theory, e.g. random utility theory, still offers at least a very usable framework for modelling. We also elaborated on the fact that choice behaviour can be habitual. It seems important to acknowledge the fact that habit can also exist in stable environments.

In the Chapter 5 we will deal with the implications of our findings thus far, and will formulate the necessary assumptions to specify a model.
Towards a Model Specification

5.1 Introduction

In the previous chapters a number of theoretical notions were presented which are necessary to formulate the framework of the proposed model. This chapter constitutes a bridge between the forgoing chapters and Chapter 6, in which a comprehensive specification of the model will be presented. The aim of this chapter is to summarize the major findings of the previous chapters, to indicate the meaning of these findings for the model, and to present the assumptions which guide the model specification.

5.2 Assumptions and Foundations

Chapter 2 dealt with information systems. It was shown that a broad variety of road user information systems exist and are under development. It had already been decided to focus only on systems that provide information relevant to route and departure time choice. It was stated that, in general, these information systems provide descriptive and/or prescriptive information. Descriptive information was defined as information about the state of (a part of) the transport system (e.g. "2 kilometer queue before Coentunnel"). Prescriptive information tells drivers what to do (e.g. "follow A10-West"). Also, information may be a mixture of both types (e.g. "follow A10-West, since there is 2 kilometer queue before Coentunnel"). It was stated that any message from an information system can be decomposed into a set of prescriptive and descriptive messages.

Since, the proposed model aims to deal with the effects of specific information on driver route choice and departure time choice behaviours, this means that the model must at least be suited to deal with prescriptive and descriptive messages.
Chapter 2 also showed that information may vary in its timing and location. Messages may be provided before departure or during the trip and be transmitted at home, within the car or at the road side. This means that the model must be suited to deal with pre-trip and en-route information.

Chapter 3 discussed the current state of transport modelling approaches. In this chapter it was shown that modelling approaches can be classified according to three main characteristics: (a) static versus dynamic approaches; (b) deterministic versus stochastic approaches; (c) equilibrium versus non-equilibrium approaches.

Concerning the first characteristic, it was stated that two types of dynamics are relevant to route choice: within day and day-to-day dynamics. For departure time choice only day-to-day dynamics are relevant. By definition, static models ignore temporal fluctuations (dynamics) in traffic flows. Therefore they are unsuited to deal with dynamic information systems. It was concluded that a dynamic modelling approach is imperative for our research goal.

Discussion of the second characteristic showed that deterministic approaches assume travellers to be perfectly informed utility maximizers. Such an approach is unsuited to deal with the effects of information provision. A stochastic approach therefore seems necessary, since this adopts a less strict position. Though stochastic approaches assume that travellers are utility maximizers, they are not necessarily perfectly informed. In stochastic modelling approaches travellers base their decisions on (expectations of) perceived utility. Perceived utility is usually modelled by adding a stochastic error term to the utility of each alternative, though the question can be raised whether travellers are (only) utility maximizers (see Chapter 4). If not, present stochastic approaches may at least be incomplete. It was decided that the concept of (expected) perceived utility is applicable as one of the model foundations. However, several reservations were made. In stochastic approaches uncertainty, and to some extent ignorance, are modelled by adding a stochastic error term. However, information provision means more than reduction of the variance of the error term. This already followed from the discussion of information systems in Chapter 2. The model should deal with the relationship between utility, information, uncertainty and ignorance more thoroughly than has been done thus far. Secondly, next to utility maximization other decision rules may be necessary to the model.

In the discussion of the last characteristic, equilibrium versus non-equilibrium approaches, it was stated that in environments in which dynamics and information are important, the modeller’s main interest should be directed towards the process, the development of travel behaviours over time, and not towards some final (equilibrium) solution. Equilibrium approaches are unsuited for our purposes.

A general conclusion from Chapter 3 is that currently no general framework exists in which route and departure time choice can be modelled in environments with provision of explicit information. In this context three major lines of research were discussed. The first line is represented by the work of Mahmassani (e.g.
Mahmassani & Shen-Te Chen, 1992; Mahmassani & Stephan, 1988), which is mainly based on Markov-type models. Particularly the specification of the feedback of trip experience to expectations in this work seems worthwhile, and will be adopted in our framework. A major shortcoming of this work is that 'complete information systems' are used. To provide drivers with complete information all the time seems unrealistic. The reason why complete information systems are used is that Mahmassani has not attempted to model driver expectations about trip performance internally. Consequently, in such a model drivers do not have their own expectations, and must be provided with complete information at all decision points. To overcome this drawback, the representation of internal expectations about performance is a necessary component in a model that deals with information.

The second line of research is by Ben-Akiva et al. (Ben Akiva et al., 1984) who have proposed an analytic approach to the problem. We concluded that this will not be the way to achieve progress. Such an approach is directed towards an equilibrium solution. Contrary to Ben-Akiva et al. we propose a simulation approach to the problem. Such an approach is targeted on the processes that occur when drivers make decisions repeatedly, and not on a solution or "final" state.

The last line of research that was discussed is by Cascetta (Cascetta et al, 1992) who specified a promising dynamic modelling framework. The main emphasis in their work lies on the loading part, and they failed to model a specific information system and consequently modelled information as error variance reduction. It was already stated that, in our view, information provision means more than error variance reduction and therefore Cascetta’s framework cannot be adopted.

Chapter 4 dealt with dynamic decision making from a psychological point of view. The major objective of the chapter was to attempt to take into account relevant findings from behavioural sciences in order to improve the behavioral foundation of the proposed model. Though extensive literature on decision making in general exists, dynamic decision making seems a neglected research area. Few facts and a far greater number of assumptions resulted from this chapter. These assumptions will constitute the behavioral basis for the proposed model.

A basic assumption that was made is that route and departure time choices are intelligible and goal directed. Rapoport's (1975) definition of dynamic decision making in which decisions are made sequentially in time, in which the task specifications may change over time, either independently or as a result of previous decisions, in which available information may be contingent on the outcome of earlier decisions, and in which implications of any decision may reach into the future, was adopted for route and departure time choice modelling. This definition implies that both choice and learning from experience must be part of the model. In this context learning may be described as updating knowledge from experience or from exogenous information. It was assumed
that individual 'knowledge' which is relevant to route and departure time choice can be divided into two components: knowledge on structure and expectations about performance. Given an individual contemplating a trip between a certain origin and destination, the knowledge on structure is the known network, which is the network that consists of all known routes between this origin and destination. The expectations about performance are the expected values of the attributes of utility, such as for instance travel time.

In situations without external information systems, knowledge on structure is assumed to be fixed, while expectations about performance may change. This means that without information the number of known routes does not change over time, but expectations of the performance of each route can change. It will be assumed that expectations only change after experience. Also, it will be assumed that the extent to which expectations change from experience to experience depends on two things: the weight given to an average of previous expectations and the weight given to the most recent experience.

In Chapter 4 it was shown that many different choice theories exist. Generally, these can be divided into normative and descriptive. It was agreed that we are greatly in need of an appropriate descriptive choice model, but such a model has not been developed yet. At present the normative expected utility maximization model seems the most used, and best available option in this context. Major advantages of this model are that it is computationally easy to handle and that necessary data may not be too difficult to collect. Due to its compensatory nature the model deals with different utility attributes in a straightforward way and is suited to deal with (ratio) scalable attributes. The validity of the expected utility maximization model for a number of choice problems has been criticized for these same reasons. In our view, the more general point of critique to many decision rules follows from the fact that decisions are only to a limited degree the result of conscious trade-offs (e.g. Rasmussen et al. 1987). Particularly, choices which are made repeatedly over time (e.g. commuter route choice) will not require the high level of cognitive processing which is implied by utility maximization all the time. Therefore, utility maximization cannot be the only decision rule which operates within the model. It is assumed that low level cognitive processing exists and can be modelled as habitual choice behaviour. The extent to which drivers make habitual choices is assumed to depend on the strength of habit for each alternative. Habit strength may change over time.

It is assumed that the first time any choice is made habit is absent (i.e. habit strength is zero). Further, the build-up and decay of habit depend on when and how often a certain alternative was chosen.

In summary, for model specification purposes we assume that at least two decision rules can be operational: expected utility maximization or habitual choice. Which of these rules is operational depends on individual choice characteristics, e.g. how many times a certain route or departure time-route
combination has been chosen in the past. The expected utility maximization rule allows us to enter descriptive traffic information into the individual choice process. Of course this can lead to additional utility attributes. For instance if queue length information is provided by an information system, such information should be entered as a component of the expected utility. At this point the assumptions concerning the first two decision rules, expected utility maximization and habitual choice, have been presented.

A new situation arises when prescriptive information is provided to drivers. Since prescriptive information tells drivers what to do, they must either comply with the advice or ignore it. It is evident that such information cannot be entered as a straightforward element of the expected utility of drivers. Therefore, when prescriptive information is provided to drivers a third choice rule may become operational: compliance, i.e. follow or ignore the advice. The degree to which drivers comply will probably depend on the credibility of the information, and credibility will probably be contingent on experiences with similar information. Table 5.1 indicates that expected utility maximization and habitual choice are feasible decision rules in all situations distinguished.

In situations without exogenous information, choice is necessarily either based on expected utility maximization or habit. In situations with external prescriptive information one additional decision rules may apply. This rule is compliance, i.e. the driver follows the advice given by the system, and may overrule expected utility maximization and habit.

**Table 5.1: Applicability of decision rules in three choice situations**

<table>
<thead>
<tr>
<th></th>
<th>no information</th>
<th>prescriptive</th>
<th>descriptive</th>
</tr>
</thead>
<tbody>
<tr>
<td>expected utility maximization</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>habitual choice</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>compliance</td>
<td>no</td>
<td>yes</td>
<td>no</td>
</tr>
</tbody>
</table>

For situations in which descriptive information is provided, we assume a direct link between expectations and descriptive information. Descriptive information influences the corresponding attributes of performance expectations. For example, exogenous travel time information may replace expected travel time. The magnitude of compliance and the extent to which external information is used to update the expected values of utility depends on the credibility of the information system. Credibility is assumed to be dependent on the discrepancy between performance which is implied by the information on the one hand, and expectations and experiences on the other.
It is assumed that both prescriptive and descriptive information can enlarge knowledge on structure. A more complex assumption which must be made in this context is that if drivers know a number of routes, they also know all combinations of these routes. This assumption allows a more convenient description of knowledge as such, and a more convenient integration of knowledge and information, as will become clear in Chapter 6.

5.3 Summary of Goals, Foundations and Behavioural Assumptions

Goals:
The model:
- must deal with route choice and departure time choice behaviour in situations with and without exogenous information;
- must be suited to deal with prescriptive and descriptive messages;
- must be suited to deal with pre-trip and en-route information;

Foundations:
- A dynamic, stochastic, non-equilibrium modelling approach is adopted.
- A simulation approach is chosen
- it is a necessary to model internal expectations about performance

Behavioral assumptions:
- Individual knowledge can be divided into (a) knowledge on the structure of the network and (b) expectations about performance.
- Learning, which is updating knowledge using experience or exogenous information, must be part of the model.
- Three decision rules may be operational: choosing out of habit, choosing out of expected utility maximization (and using external information when present) and compliance with advice (when present).
- Which rule is operational depends on individual choice and situational characteristics.

In situations without external information systems it will be assumed that knowledge on structure is fixed, while expectations about performance may change. Expectations only change after experience, and the extent to which expectations are influenced by experience depends on two things:
\begin{itemize}
  \item[i] the weight given to previous expectations;
  \item[ii] the weight given to the most recent experience.
\end{itemize}
- It is assumed that the extent to which drivers make habitual choice depends on the properties of habit, which are:
  \begin{itemize}
    \item[i] the build-up and decay of habit;
    \item[ii] the maximum strength of habit.
  \end{itemize}
Decision rules in situations without exogenous information:
- Drivers either maximize expected utility or make a habitual choice;
- It is assumed that the first time any choice is made habit is absent;
- The build-up and decay of habit depend on when and how often a certain option was chosen

Decision rules in situations with prescriptive information:
- prescriptive information potentially overrules expected utility maximization and habitual choice;
- When drivers follow a prescriptive message the corresponding decision rule is compliance

The general structure of the assumed choice process is depicted in Figure 5.1.

**Figure 5.1** General description of the assumed choice process

The relations between the entities present after a choice was made and following update procedures are depicted in Figure 5.2.

In the next chapter we will specify the proposed model in detail.
Figure 5.2 Relation between entities and the updating procedures
Model Specification

6.1 Introduction to the Chapter

From the assumptions put forward in the previous chapter a model was developed to simulate route and departure time choices in environments with and without information systems. This chapter presents the model in detail. To provide a clear and comprehensive description of the model, the chapter is divided into two parts. Sections 6.1 through 6.9 provide a primarily verbal, non-mathematical account of the model which is intended for readers who have limited mathematical knowledge. Necessarily, this account leaves some questions unanswered concerning the details of mathematical and computational procedures. However, it does provide a full, conceptual description of the model. The second part of the chapter, starting at 6.10, provides the complete mathematical and computational formulation of the model and aims at those readers who are familiar with mathematical set notation and the formulation of procedures and algorithms. Both parts of the chapter may be read independently, though reading of the first part may enhance understanding of the second.

6.2 Part I: Outline of the Model

In this section a general outline of the model is presented to provide understanding of the structure of the model and the linkage of sub-processes. All sub-processes will be addressed comprehensively in the following sections.

The model simulates individual route and departure time choice behaviours in transport environments with and without exogenous information systems, for a number of drivers over time, i.e. from day to day. Furthermore, the model output is the result of these individual behaviours. The model endeavors to be a tool to assess the impact of descriptive and prescriptive information of
varying quality over time, which is provided either before departure or en route.

![Diagram]

Figure 6.1 General overview of the model for environments without exogenous information

The overall process structure of the model is depicted in Figure 6.1. Processes are depicted as rectangles and are connected with bold arrows. Data are depicted as rectangles with blunt corners and their relation to processes with hollow arrows. For all individuals an origin, destination and preferred arrival time are assumed known. To start the model an initial state must be assumed. This initial state defines 'expectations' at the first day $t$.

Route and departure time choice are performed in the process 'choice'. Choice is based either on 'expectations' or results from 'habit'. Expectations involve two distinct types of data. First a limited set of known routes. This set reflects individual knowledge on the structural properties of the network known to the individual. This kind of knowledge will be referred to as knowledge on structure. Second, expectations are determined by perceived utilities of choice options. Perceived utilities simulate individual expectations about the state of the network at a certain timeslice and day. In contrast to knowledge on structure, this kind of knowledge will be referred to as expectations. Expectations may involve several so-called attributes, e.g. mean expected travel times, travel time variances. Expected utility is a weighted sum of all attributes. Which attributes are used depends on the application. Values of mean expected travel time and travel time variance are time and day dependent due to day to day and time of day
dependent travel time patterns. For instance, travel times are generally larger during peak than off-peak hours and working day travel time patterns differ from weekend patterns. The model allows the researcher to decide how many of these 'registers' are necessary. Whether people will maximize perceived expected utility or make a habitual choice, i.e. simply do what they have done before, depends on the strength of 'habit'. The strength of habit is determined by the number of times the same choice was made before and the number of different choices in between these two same choices.

![Diagram](image)

**Figure 6.2** General overview of the model for environments with exogenous information

After a route and departure time have been chosen, 'trip performance' takes place, resulting in some experienced travel time and arrival time. Over time, expectations may change as a consequence of these experiences. Adjustments of mean expected travel times and knowledge about travel time variances due to variations in experienced travel times are made in 'expectation update'. Also over time, the strength of habit may change if certain routes are used frequently by the same individual. 'Habit update' computes new habit strengths after trips have been performed.

When exogenous information is present the model becomes more complicated.
(see Figure 6.2). On a more detailed level than is depicted in Figure 6.2 descriptive and prescriptive information influence the choice processes as they take place without information in different ways. Also some similarities exist. Both types of information may provide drivers with new knowledge on the structure of the network, since any message concerns specific parts of the network. These parts may or may not be known to the individual.

Expectations are influenced by descriptive information. Descriptive information may be incorporated in expectations for a specific choice. Prescriptive information may overrule completely the choice process in environments without information. In fact, reactions to prescriptive information are modelled as compliance with a certain advice: drivers either follow the advice or do not. The degree to which any type of information influences the choice process depends on the 'information evaluation'. This evaluation pertains to: (i) the discrepancy between the individual's expectations and the transmitted information, and (ii) the quality, or credibility, of information. Of course, these two are not stable over time because they are directly related to expectations and thus to experienced travel times and arrival times. Section 6.16 will elaborate further on evaluation of information and compliance.

The dynamic character of the knowledge on the structure of the network, expectations about trip performance, strength of habit, availability of exogenous information and perceived quality of information can be generally represented by a state describing the individual at a certain time. In summary, the route and departure time process is based on individual states that may change due to experience and exogenous information and consists of the following subprocesses and data structures:

- knowledge on structure, initial values and update process
- expectations, initial values and update processes
- habit strength, initial values and update process
- compliance, initial values and credibility update process
- habitual choice
- utility maximization
- route choice
- departure time choice
- trip performance

All sub processes will be discussed in the following sections. Although route and departure time choice processes operate pseudo-simultaneously, sub processes will first be described separately for reasons of clarity. Next, the impact of descriptive and prescriptive en route and pre trip information will be discussed for each process. Subsequently, the way in which route and departure time choice processes are merged into one single computational routine is presented. Finally, the way in which the choice processes are linked to a dynamic route
loading procedure will be discussed.

6.3 Generation of Knowledge on Structure

Choices can be made only if individuals have knowledge on structure. To simulate this knowledge a limited, fixed set of known routes (see also Bovy & Stern, 1990; Richardson, 1982) is calculated for each individual per OD-pair. To perform this calculation an algorithm developed by Lawler (1972) is used. The result of this algorithm is a set of $M$ best routes. A following procedure determines a subset of $m$ routes that are known to individual $i$ (Figure 6.3).

![Diagram showing $m$ known routes from $M$ best routes]

*Figure 6.3* $m$ known routes from $M$ best routes

For the present description of the choice set generation process, the method to find the *quickest* routes will be briefly presented. However, other attributes, like costs, distances etc. can be substituted or added easily and do not complicate the method.

The outcome of the complete process is a set of $m$ routes known by an individual and for this set holds that the probability that the set contains a quicker route is larger than the probability that it contains a longer route, and sets may differ for individuals with similar OD-pairs. To determine a set of quickest routes, travel times must be assigned to all links in the network. In some cases mean travel times may be available from traffic measurement data or other reports, while these data may also be available from transport models. For simulation purposes it is necessary that researchers can also apply the model if these data are not available. In that case, a static deterministic user equilibrium (SDUE)-assignment procedure (see Chapter 3) is utilized to calculate travel times per link. In such a procedure all individuals that are to be modelled are represented in a trip-matrix comprising all trips between all OD-pairs for different time slices. This trip-matrix is assigned to the network, and a traffic flow-pattern over the various links within the network results. Because there is a direct
relationship between traffic-flow and travel time, the travel times that are necessary to calculate the quickest routes are then available. The general idea behind the algorithm that actually calculates these routes is that the quickest route is first calculated from the complete set of all routes. Next, this route is deleted from the complete set and the remainder is partitioned into a number of subsets, each excluding one or more links of the previously determined quickest route. Then for each partition the quickest route is determined. The algorithm stops when the required $M$ routes have been determined. For mathematical details of the algorithm readers are referred to the second part of this chapter.

Likewise, to perform departure time choice, individuals must have access to a set of feasible departure time options. It is easy to understand that route choice sets by definition have discrete size, while departure time choice sets have not. Even within small departure time choice intervals people have an infinite number of departure time options. From a behavioral point of view it seems unlikely that people optimize departure time along a continuous time axis. Therefore, the departure time choice set is represented as a discrete set within the model.

In the model the approach is adopted that departure times are derived from preferred arrival times instead of the other way around. Within the departure time choice process, first an acceptable arrival time interval is determined from the preferred arrival time, which is assumed known. The size of such intervals may be determined from earlier studies, for instance by Hendrickson & Kocur (1981) and Hendrickson & Plank (1984) (see Figure 6.4).

![Diagram](image)

**Figure 6.4** Utility as a function of arrival time

Next, this interval is divided into a small, discrete number of sub intervals,
and the middle of each interval represents one arrival time choice option. How the model deals with departure time choice will be discussed in Section 6.8.

6.4 Initial Values

The simulation of the day to day choice process necessarily starts at a certain point in time. The researcher may sometimes already have more or less clear ideas about the initial states of the individuals that are to be modelled. For instance when individuals are assumed to be already very familiar with the trips they perform, e.g. when commuters are modelled. In other cases, when new and hence unknown parts of a network are involved, initial states may be unknown to the researcher. In all cases, to start the choice process initial values for mean expected travel time, travel time variances, strength of habit and credibility of the various types of information must be available or assumed. Horowitz (1984) has already provided evidence for the importance of initial values for simulation results although at this time no final conclusions can be drawn concerning this problem. Of course, researchers are free to experiment with initial values within the model, though some discussion will need to be devoted to each value chosen.

For simulations in which the start of the choice process represents a point in time for which a history of choices may already be assumed, mean expected travel times and travel time variances may be available from other data sources or transport models. If such a history is not evident some initial value must simply be assumed. In such cases free flow travel times may be presumed to serve as initial values for mean expected travel time and the square root of the mean expected travel time may serve as an initial variance estimate.

When a history of choices can be assumed, strength of habit may already be at a maximum. In such instances this maximum may serve as an initial value. In those cases in which the researcher assumes no history of choices, habit strength can be assumed nil. The way in which habit strength is simulated will be discussed in Section 6.14.

For new information systems data on the credibility of the information provided by these systems are unavailable. The model allows the researcher to input either optimistic or pessimistic views about credibility.

6.5 Perceived Utility Maximization

To make a choice between two or more alternatives a choice rule must be applied. For environments without exogenous information two rules apply: perceived utility maximization and habitual choice. If prescriptive information is available a third choice rule, compliance, becomes operational. This section discusses
the first rule, perceived utility maximization, while Section 6.6 discusses habitual choice. Compliance will be discussed in Section 6.9.

Utility maximization follows from random utility theory (Manski, 1977; Horowitz, 1985). Perceived utility for individual $i$ and route $r$ at time $t$, ($U_{itr}$), is assumed to be a weighted sum of attributes. Attributes may be mean expected travel time ($\mu_{itr}$) and travel time variance ($s_{itr}^2$). Further a normal distributed, individual and route specific and time dependent random error is added.

$$U_{itr} = \beta_1 \mu_{itr} + \beta_2 s_{itr}^2 + \epsilon_{itr}$$

Drivers do not optimize their route choice solely on the basis of expected utility, i.e. mean expected travel time and travel time variance. In fact, there will exist 'natural' variance in expected utilities, e.g. random perceptual errors and personal preferences. Such variances are represented as an error term, so the sum of expected utility and error constitutes perceived utility. The error term may further represent personal preference or aversion for a certain route, and idiosyncratic variations in route preferences.

Other attributes may be added to perceived utility without loss of generality. Perceived utility maximization simply means that individuals will choose routes with the highest perceived utility.

### 6.6 Habitual Choice and Updating Habit

The second choice rule within the model is habitual choice. Sometimes if not often individuals will not maximize perceived utility but will make a habitual choice. Habitual choice means that there is a certain probability that individuals choose the same route- and departure time option simply because they have done so before. No comparison of perceived utilities of different options will be carried out. This type of behaviour results from what may be called habit strength.

Habit strength equals the probability that a person makes a habitual choice. Variation in habit strength is a result of three factors. The habit strength for a route increases with the number of times the route has been chosen before, and decreases with the number of different route choices that have been made since that route was last chosen. The third factor that influences habit strength is the experienced travel time following from the route choice (see 6.2).

$$e\tau_{itr} - \mu_{itr} \leq \eta$$

Habit strength increases only if the experienced travel time, $e\tau_{itr}$, is not some threshold value greater than the mean expected travel time $\mu_{itr}$. This implies that people will only adhere to habitual choice if the outcome of such choices will not become some threshold worse than their expectations. Zero habit strength indicates absence of habit and route choice will necessarily be made
based on perceived utility maximization. Habit strength approaching a value of one may lead to highly stable habit-based route choice behaviour.

6.7 Updating Expectations

Irrespective of the choice rule operating, individuals learn from their experiences. Learning from experience pertains only to expected utility, i.e. mean expected travel time and travel time variance, because the error term is assumed to be not correlated with experience. After each performed trip, the experienced travel time is used to update the mean expected travel time and the travel time variance for the chosen route. Mean expected travel time is calculated as a weighted sum of the previous mean expected travel time and the preceding experienced travel time (cf. Horowitz, 1984). Likewise, travel time variance can be updated according to experienced travel time. An example for expected travel time is denoted in (6.3), with \( tt_{tr,t-1} \) the expected travel time at day \( t-1 \), for route \( r \) and individual \( i \) and \( ett_{tr,t-1} \) the experienced travel time for the same combination of day, route and individual.

\[
\begin{align*}
  tt_{tr} &= \psi tt_{tr,t-1} + (1-\psi) ett_{tr,t-1} 
\end{align*}
\]  

(6.3)

The weights used within the updating procedure sum to one, and are related to the importance of the last experience (\( \psi \)) versus the importance of the last expected value (\( 1-\psi \)).

6.8 Departure Time Choice and Route Choice

Departure time choice is formulated as a discrete choice process. Therefore it does not fundamentally differ from route choice. When departure time choice is conceived as a discrete choice process an (arbitrary) number of intervals on the time axis must be specified. These intervals serve as individual choice alternatives.

Within the model the problem of departure time choice is reversed to an arrival time choice problem. The choice between arrival time or departure time is arbitrary. The advantage of an arrival time approach is that schedule delay\(^1\) can be computed directly, once a preferred arrival time has been determined.

In a situation without exogenous information arrival time choice is modelled in a similar way as route choice: either from habit or because of highest perceived utility. The way habit is modelled in the arrival time choice process is identical

\(^1\) schedule delay is a function of the time an individual comes either too late or too early
to the way in which habit is modelled in the route choice process. Also the way in which perceived utility maximization is modelled does not fundamentally differ, although the utility function is somewhat more complex. Within the model the utility of an arrival time interval is a weighted sum of the utility of the route that would be chosen for that interval, and the expected schedule delay for that interval.

The intervals that serve as choice alternatives are projected around the preferred arrival time and are a partition of the interval \([PAT - \alpha r_1, PAT - \alpha r_2]\) that is determined from a maximum schedule delay penalty \(D\) (see Figure 6.4).

The update procedures as well as the way in which information is processed are the same as those for route choice.

From the chosen arrival time - route combination the departure time is determined as follows: for an arrival time \(AT\) and route \(r\) with expected travel time \(tt_{r,AT}\) the departure time becomes \(AT - tt_{r,AT}\).

### 6.9 Credibility of Information and Compliance

Descriptive and prescriptive information influence route and departure time choices in different ways. If descriptive information is acknowledged as relevant by individuals, they may incorporate it into the perceived utility of alternatives for the subsequent choice. If for instance an information system provides a travel time, this travel time can replace the mean expected travel time and reduce expected travel time variance to zero for the subsequent choice. The degree to which this will happen depends on the credibility of the information, while the credibility of the information is influenced by previous experiences with the information system. The more credible the information is perceived to be, the more likely it is that the information will replace travel time and variance in the expected utility. Drivers can evaluate experiences with descriptive information only if they actually drive a route for which the information was provided. Evaluation of descriptive information in that case is modelled as follows. If the absolute value of the difference between provided travel time \((TT)\) and experienced travel time \((ett)\) is more than some threshold \(\omega\), so if \(|TT - ett| > \omega\), the information will be evaluated as unreliable. If the driver does not select a route for which the information is valid, there is no way to evaluate the credibility of this information.

Prescriptive information tells the driver what to do at a certain time, and can overrule perceived utility maximizing completely. If so, the individual will comply with the offered advice. Otherwise, the currently operating choice rule will remain valid. Again, the degree to which this will happen depends on the perceived credibility of the information, and the perceived credibility is influenced by previous experiences with the information system (Figure 6.5).
Figure 6.5 Compliance update scheme

Exogenous information can influence route and departure time choices at different moments in the choice process. Though departure time choice can only be influenced by information before the trip is started, route choice information can be influenced either before the trip is made or en route.
6.10 Part II: Introduction

In the second part of this chapter the model will be formulated completely, both in a mathematical and procedural manner. In the Sections 6.11 through 6.17 there is no mention of departure time, nor of the time and place an information message is sent. A fixed departure time is assumed. Starting with 6.18 departure time choice will be included. This does not cause any problems, since the structure of the model is such that choice processes and the influence of information are modelled in general, and it is relatively easy to incorporate departure time in this.

6.11 The Individual

All individuals have some knowledge of the transport environment. This knowledge relates to structure and expectations. In environments where external information sources are available, individuals may access this information on the structure and expectations of the transport system. Generally, at time $t$ individual $i$ is in state $S_{it}$:

$$S_{it}=(KS_{it}, E_{it}, H_{it}, IS_{it}, I_{it}) \tag{6.4}$$

with

- $KS_{it}$ knowledge on the structure of the transport system, i.e. the known network and routes, that individual $i$ has at time $t$.
- $E_{it}$ expectations, i.e. expected values of utility attributes of all links and routes in the known network, that individual $i$ has at time $t$.
- $H_{it}$ choice history of the individual. It is assumed that this history is related to habitual behaviour. Therefore, $H_{it}$ is the set in which the strength of habit for individual $i$ is listed for each known route.
- $IS_{it}$ exogenous information on structure that $i$ has access to at time $t$.
- $I_{it}$ exogenous information on performance $i$ has access to at time $t$.

6.12 Knowledge on Structure

The first time an individual $i$ chooses a route between $o$ and $d$, the known network $D_{it}$ must be defined. To do this, the initial set of known routes $KS_{it}$ must be defined. In network $D$ the set $\Lambda(D)$ denotes the set of all routes between $o$ and $d$. This set may be very large and hard to determine. To simplify things, a subset of $\Lambda(D)$ containing the $M$ best routes is determined.
To define a best route, a travel time must be assigned to each link in \( L(D) \). This is done as follows: all individuals present in the model, i.e. all individuals travelling between all \((o,d)\)-pairs, form a trip-table. For each link \( l \) in the network a capacity and a flow-dependent travel time function is defined by \( t(C_l, q_l) \), where \( C_l \) denotes the capacity of \( l \) and \( q_l \) the traffic flow on \( l \). The flows and resulting travel times for all \( l \) are determined by a static deterministic user equilibrium assignment, yielding also \( T \), the set of travel times for all links.

Let \( \lambda(D) \) denote the ordering of \( \Lambda(D) \) according to \( T \). Suppose \( \lambda(D) = (r_1, r_2, \ldots) \). To determine \( \tilde{\lambda}_m(D) = (r_1, \ldots, r_m) \), the \( M \) best, i.e. quickest, routes, the algorithm proposed by Lawler (1972) is adopted.

**Step 1** *(Start)*

Assign the travel times in \( T \) to all links. Find the shortest route \( r_i \) from \( o=1 \) to \( d=n \) using Dijkstra’s algorithm (Dijkstra, 1959) and place in LIST and set \( m = 1 \).

**Step 2** *(Output \( m^{th} \) shortest route)*

If LIST is empty, stop; there are no more routes from \( l \) to \( n \). Otherwise, remove the shortest route in LIST and output this route as \( r_m \). If \( m = M \) stop, the computation is completed.

**Step 3** *(Augmentation of LIST)*

Suppose without loss of generality that \( r_m = (1, 2), (2, 3), \ldots, (q-1, q), (q, n) \) and that \( r_m \) is the shortest route subject to the conditions that it is forced to include the links \((1, 2), (2, 3), \ldots, (p-1, p)\), where \( p < = q \), and that certain links from node \( p \) are excluded. (These conditions are stored in LIST with \( r_m \))

If \( p = q \) find shortest route from \( 1 \) to \( n \) subject to the conditions that \((1, 2), (2, 3), \ldots, (p-1, p)\) are included and that \((p, n)\) is excluded, in addition to the links from \( p \) already excluded for \( r_m \). If there exists such a route place it in LIST with its conditions.

If \( p < q \) find the shortest route subject to

1. \((1, 2), (2, 3), \ldots, (p-1, p)\) included and \((p, p+1)\) excluded, plus the links that were excluded for \( r_m \)
2. \((1, 2), (2, 3), \ldots, (p, p+1)\) included and \((p+1, p+2)\) excluded, plus the links that were excluded for \( r_m \)
3. \((q-p-2)\) \((1, 2), (2, 3), \ldots, (q-2, q-1)\) included and \((q-1, q)\) excluded, plus the links that were excluded for \( r_m \)
\[(q-p-I), (1,2), (2,3), \ldots,(q-I,q) \text{ included and } (q,n) \text{ excluded, plus the links that were excluded for } r_m\]

Place each of the shortest paths in LIST, together with the set of conditions under which it was obtained. Set \(m=m+1\) and return to step 2.

The complexity of this algorithm is \(O(Mn^2)\) (Dijkstra’s shortest path algorithm is \(O(n^2)\)). Applying the above algorithm yields \(\hat{\Lambda}_M(D) = \{r_1, \ldots, r_M\}\). To define \(KS_{II}\), the initial set of known routes for individual \(i\), first the set \(R_i \subseteq \hat{\Lambda}_M(D)\) is defined. It is easy to see that in general \(\Lambda(\lambda(R_j)) \neq R_i\). Therefore the set \(KS_{II}\) is constructed from \(R_i\), with \(R_i \subseteq KS_{II}\) such that \(\Lambda(\lambda(KS_{II})) = KS_{II}\) by defining \(KS_{II} = \Lambda(\lambda(R_j))\).

The route set \(R_i\) is constructed as follows: the probability that \(i\) knows a quicker route is larger than the probability that \(i\) knows a slower route. Thus,

\[
\Pr(r_j \in R_i) \geq \Pr(r_{j+1} \in R_i) \quad \forall \ i,j \ 1 \leq j \leq M-1
\]  

Further, \(|R_i| = m_i\) is assumed. The above assumptions can be met by applying the following procedure:

---

**Step 1**  \(\text{ (Initialization)}\)

\[
R_i \leftarrow \emptyset
\]

\[
j \leftarrow 1
\]

\[
\forall r_i \in \hat{\Lambda}_M(D) : P_i \leftarrow \frac{e^{-\alpha t_i}}{\sum_{j=1}^{M} e^{-\alpha t_j}}
\]

---

**Step 2**  \(\text{ (Fill route subset)}\)

draw random \(\eta \in U(0,1)\)

determine \(k = \min\{l | \sum_{i=1}^{l} P_i \geq \eta\}\)

\[
R_i \leftarrow R_i \cup \{r_k\}
\]
Step 3  (Update probabilities)
\[ \forall r_i \in \Lambda M(D) : P_i \leftarrow \frac{P_i}{1 - P_i} \]
\[ P_k \leftarrow 0 \]
\[ j \leftarrow j + 1 \]

Step 4  (Stop)
if \( j < m_i \) then goto 2
else stop

Thus combining the above observations for each individual a set \( KS_{il} \) can be constructed that consists of known routes. Instead the known network could also be used since \( KS_{il} = \Lambda(\lambda(KS_{il})) \) and \( D_{il} = \lambda(KS_{il}) \).

Knowledge on structure can only increase by exogenous information systems. How such an increase can be modelled is described in 6.15.

6.13  Expectations

The expectations, \( E_{it} \), are represented by expected utilities of \( L(D_{it}) \), the set of links of the known network \( D_{it} \), known to individual \( i \). Thus \( E_{it} = \bigcup_{l \in t(D)} \{ V_{ilt} \} \).

For example a utility function may incorporate two attributes, expected travel time and expected travel time variance:
\[ V_{ilt} = \beta_1 t_{ilt} + \beta_2 s_{ilt}^2 \]  \hfill (6.6)
with \( t_{ilt} \) the expected travel time and \( s_{ilt}^2 \) the expected travel time variance on link \( l \). \( E_{it} \) incorporates the expected utilities of all known routes: \( V_{it} = \sum_{l \in r} V_{ilt} \).

Individuals have expectations of utilities of all links in the known network, have initial expectations of utilities, and learn from experience. Learning from experience means that the mean expected travel time is \( t_{it} = f(t_{it}, ett_{it,1}, \ldots, ett_{it,l-1}) \), with \( ett_{it,l} \) being the experienced travel time for link \( l \) on day \( t \). Thus the expected travel time for link \( l \) is a function of all prior experiences on that link and the initial expected travel time. An experience \( ett_{it} \) does not exist for all \( t \). Thus,
\[ t_{it} = f(t_{it}, \bigcup_{r=1}^{t-1} \{ ett_{ir} \}) \text{ with } \delta_{it} = 1 \text{ when link } l \text{ was chosen on day } t \text{ by individual } i \text{ and } 0 \text{ otherwise.} \]
A similar relationship holds for the travel time variance. Expected variance follows from all experiences and the initial expected
variance. So $s_{it}^2 = g(s_{it}, \bigcup_{t=1}^{t-1} \{ett_{it}\})$.

So far, a learning module has been described by two functions $f$ and $g$. Following Horowitz (1984) we define for travel time:

$$tt_{it} = \delta_{it,t-1} [\psi tt_{it,t-1} + (1 - \psi) ett_{it,t-1}] + (1 - \delta_{it,t-1})tt_{it,t-1}$$  \hspace{1cm} (6.7)

or

$$tt_{it} = tt_{it,t-1} + \delta_{it,t-1} (1 - \psi) \{ett_{it,t-1} - tt_{it,t-1}\}$$  \hspace{1cm} (6.8)

Obviously both (6.7) and (6.8) require an initial value $tt_{it}$. It will be highly dependent on the situation what exactly these initial values are.

From (6.7) it can be derived that after $t-1$ experiences the weight, or importance, of the $j$th experience (when present), is $\psi^{t-1-j}(1-\psi)$ for $j > 1$. To update expected travel times only the previous average and previous experience are necessary. This simplifies the computational process to a large extent.

Using this weight in the common formula for variance the following can be derived:

$$s_{it}^2 = \frac{\psi^{t-1}(tt_{it} - tt_{it,t-1})^2 + \sum_{j=1}^{t-1} \psi^{t-1-j}(1-\psi) \delta_{ij} (ett_{ij} - tt_{it,t-1})^2}{\psi^{t-1} - \sum_{j=1}^{t-1} \psi^{t-1-j}(1-\psi) \delta_{ij}}$$  \hspace{1cm} (6.9)

Contrary to the updating of expected travel times, the above definition of updating variance would require a full description of all experiences, $ett_{it}$, $\forall 1 \leq \tau < t-1$.

For reasons of computational convenience the following approximation will be used, where the experiences are not weighted:

$$s_{it}^2 \approx \delta_{it,t-1} \left[ \frac{t-3}{t-2} s_{it}^2 + \frac{(ett_{it,t-1} - tt_{it,t-1})^2}{t-2} \right] + (1 - \delta_{it,t-1})s_{it,t-1}^2$$  \hspace{1cm} (6.10)

Now (6.10) will be used for updating variance. Similar to expected travel time, (6.10) requires initial values for $s_{it}^2$.

### 6.14 Route Choice Without Exogenous Information

The route choice process can be split into two main branches: individual $i$ either chooses a route based on expected utility maximization, or $i$ refrains from this and performs according to habit (see Figure 6.6).
The route choice process can be summarized by stating that

$$P_{irt} = H_{it} \cdot PIN_{irt} + (1 - H_{it}) \cdot PUM_{irt} \quad (6.11)$$

with

- $P_{irt}$ probability that individual $i$ will choose route $r$ at day $t$
- $H_{it}$ habit strength at day $t$ for individual $i$
- $PIN_{irt}$ probability that route $r$ is chosen at day $t$ when individual $i$ chooses out of habit
- $PUM_{irt}$ probability that route $r$ is chosen at day $t$ when individual $i$ chooses out of utility maximization

**Expected Utility Maximization**

Using knowledge of route $t$, $E_{it}$ and $KS_{it}$, $i$ can rank known routes by expected utility in ascending order. At $t$ the individual knows network $D_{it}$. The expected utility of any route $r \in \Lambda(D_{it})$ is the sum of the utilities of all links on route $r$. So

$$V_{irt} = \sum_{l \in r} V_{ilt} \quad \forall r \in \Lambda(D_{it}) \quad (6.12)$$

All values $V_{ilt}$ are listed in $E_{it}$.

Suppose, the expected utility $V_{ilt}$ is defined as

---

$^2$ Obviously the model is independent on the choice of the utility function. The function here is an example for illustration
\[ V_{ilt} = \beta_1 t_{ilt} + \beta_2 s^2_{ilt} \]  

where
\( t_{ilt} \) the expected travel time of link \( l \) for individual \( i \) at time \( t \)
\( s^2_{ilt} \) the expected variance in travel time of link \( l \) at time \( t \)
\( \beta_1, \beta_2 \) parameters

Substituting (6.12) in (6.11) yields
\[ V_{ir} = \beta_1 \sum_{l \in r} t_{ilt} + \beta_2 \sum_{l \in r} s^2_{ilt} = \beta_1 t_{ir} + \beta_2 s^2_{ir} \]  

In order to define an expected utility maximization model we add a random error term to \( V_{ir} \). This random disturbance \( \varepsilon_{ilt} \) represents a deviation from the individual expected utility estimation. Such a deviation represents a personal preference or aversion for a certain route. Further, route choice may vary due to variations in traffic conditions, and variations in personal circumstances. Individuals depart from usual routes to mail letters, drop people off, etc. Also people may choose a different route than the one that has the highest expected utility without an obvious reason. This is called idiosyncrasy. To incorporate all this the error term is added. Thus we define the perceived (random) utility
\[ U_{ir} = V_{ir} + \varepsilon_{ir} \]  

Now \( i \) chooses route \( r \) iff
\[ U_{ir} > U_{is} \quad \forall s \neq r \]  

It is well known that when for instance \( \varepsilon_{ir} \) are independently Gumbel distributed, that (6.14) and (6.15) define a logit model. Then it holds that
\[ PUM_{ir} = \frac{e^{V_{ir}}}{\sum_{\rho} e^{V_{\rho}}} \]  

A problem may however occur with overlapping routes. In that case the random expected utility maximizing model must be a probit model, where the interdependencies of the error terms are incorporated by a correlation matrix (see e.g. Bovy, 1990).

** Habitual Choice**

Individuals do not always choose routes that have the highest expected utility. They may skip perceived utility maximizing behaviour and make habitual choices. To be able to model habit, three assumptions were made:

- \( i \) when a certain route is chosen it becomes more likely that the same route will be chosen the next time;
the likelihood that a route is chosen depends on the number of times it was chosen previously;

assumptions i and ii only hold when the experience on a route was good compared to implicitly expected utility.

We define $H_{it} \cdot PIN_{itr}$ as the probability that at time $t$ route $r$ will be chosen from habit by individual $i$. For $i$ the total strength of habit at time $t$ is

$$H_{it} = H_{it} \sum_{r \in A(D_{it})} PIN_{itr} \quad (6.18)$$

To decide whether the experience of individual $i$ with route $r$ at time $t$ is perceived as good or bad, the experienced travel time $ett_{itr}$ is compared with the expected travel time $u_{itr}$. The comparison is based on the principle of bounded rationality (Simon, 1955). We define $\sigma_{it}$ as 1 when the route chosen by $i$ at time $t$ yields a good experience and as 0 when the experience is bad.

Suppose at $t$ route $r$ was chosen, then we define

$\sigma_{it} = \begin{cases} 1 & \text{when } ett_{itr} - u_{itr} \leq \eta \\ 0 & \text{otherwise} \end{cases} \quad (6.19)$

We define the probabilities of habit for all routes recursively as

$$PIN_{itr} = \frac{\gamma P_{itr,t-1} + \delta_{itr,t-1} \sigma_{itr,t-1}}{\gamma + \sum_{\rho \in A(D_{it})} \delta_{itr,t-1} \sigma_{itr,t-1}} \quad (6.20)$$

This formula can be explained as follows: for route $r$ the amount of habit changes when this route was chosen and experience was good. This is expressed by $\delta_{itr,t-1} \sigma_{itr,t-1}$, where $\delta_{itr,t-1}$ is 1 when route $r$ was chosen and 0 otherwise. The parameter $\gamma$ determines the speed with which the distribution of habit is built up as a result of a specific choice. When $\gamma$ is large the distribution of habit over the routes is hardly altered. When $\gamma$ is small, the fact that a route was chosen and the experience was good enlarges the proportion of habit related to that route significantly.

Initially the probabilities are 0. Now for each route the sum of all prior choices is calculated, and the proportion is multiplied by the total amount of habit in the system. Further, the total amount of habit strength is defined as

$$H_{it} = H_{it}^{\max}(1 - \exp(\alpha \sum_{r=1}^{t-1} \sum_{\rho \in A(D_{it})} \sigma_{itr} \delta_{itr})) \quad (6.21)$$

The following algorithm yielding (6.18) and (6.19) was developed:
Step 1  (Initialization)
\[ t \leftarrow 1 \]
\[ g \leftarrow 0 \]
\[ \forall r \in \Lambda(D_d) : PIN_{itr} \leftarrow 0 \]

Step 2  (Choose route)
route \( r \) is chosen and performed yielding \( \sigma_{ir} \)
\[ \delta_{itr} \leftarrow 1 \]
\[ g_{i} \leftarrow g_{i} + \sigma_{ir} ; g_{i} \] is the number of good experiences
\[ t \leftarrow t + 1 \]

Step 3  (Update probabilities)
\[ \forall r \in \Lambda(D_d) : \]
\[ \text{if} \ (\sigma_{ir} = 1 \text{ and } \delta_{itr} = 1) \text{ then} \]
\[ PIN_{itr} \leftarrow PIN_{itr,t-1} \gamma + 1 \]
\[ \text{else} \]
\[ PIN_{itr} \leftarrow PIN_{itr,t-1} \gamma \]
\[ H_{ir} \leftarrow H_{max} (1 - e^{\alpha g_{i}}) \]
\[ \forall r \in \Lambda(D_d) : PIN_{itr} \leftarrow \frac{PIN_{itr}}{\sum_{\rho \in \Lambda(D_d)} PIN_{\rho t}} \]

GOTO Step 2

The importance of the last experience as formulated within the random utility function should not be confused with the importance of the last choice. The former is related to utility maximization, and the latter is related to habitual choice. We have assumed that experienced travel time and costs lead to adaptations of individual expectations. The more important the last experience is to the individual, the more impact this experience will have on following expectations. On the other hand, the importance of the last choice is part of the tendency to make habitual choices. The more important the last choice is, the more likely it is that the next choice will be the same. In this way perseverance in choice behaviour is simulated. The importance of the last choice must be distinguished from the habit concept as a whole, which also depends on the number of times a certain route was chosen in the past. The more times the same route was chosen, the more likely it becomes that it will be chosen again.

Since the importance of the last experience in the expectations update algorithm may reduce the variability within a choice series one may feel this has to do
with habit. Conceptually this is not true, because within the model habit is conceived of as a distinct decision rule.

6.15 The Relation between the Information System and the Individual

**Information on Structure**

A message from an information system under consideration consists of information on structure and the information about performance. In the model information about performance is compared to individual knowledge. Further, a message from an information system may replace the individuals knowledge to a certain extent.

Suppose information on structure $IS_{it}$ is $P$, a set of acyclic $(u,v)$-paths, with $u,v \in N(D)$. Note that not necessarily it holds that $u,v \in N(D_{it})$. Similarly as for knowledge on structure the network induced by $P$ is $\lambda(P)$. This set of paths may enlarge the set of known routes. It holds that $\Lambda(\lambda(P) \cup \lambda(KS_{it})) \supseteq KS_{it}$.

We define the amount of information on structure transmitted by a message with structure $P$ to individual $i$ in state $S_{it}$ as $I(P) = \Lambda(\lambda(P) \cup \lambda(KS_{it})) \Theta KS_{it}$. Thus $P$ enlarges the knowledge on structure iff $\Lambda(\lambda(P) \cup \lambda(KS_{it})) \supseteq KS_{it}$, or, in other words, iff $|I(P)| \geq 0$. So when a message with structure $P$ is received by individual $i$, the knowledge on structure of $i$ becomes $\Lambda(\lambda(P) \cup \lambda(KS_{it}))$.

The concept can be described by the next procedure:

\[
\begin{align*}
L & \leftarrow L(D_{it}) \\
N & \leftarrow N(D_{it}) \\
\forall p \in P: & L \leftarrow \mathcal{L}(p) \quad \text{and} \quad N \leftarrow \mathcal{N}(\lambda(p)) \\\nD_{it} & \leftarrow (N,L)
\end{align*}
\]

6.16 Descriptive Information

In Chapter 2 two kinds of information were distinguished: prescriptive and descriptive information. In model terms, descriptive messages relate primarily to individual expectations. Such messages provide, for instance, travel times or delays. When received, this information may replace corresponding individual knowledge.

Implicitly, any message also carries information on structure. Suppose the structure of a message is a set of paths $P$. Suppose $D'_{it}$ is the network induced by $P$ and $D_{it}$. When $|I(P)| > 0$ there are links $l$, with $l \in L(D'_{it}) - L(D_{it})$ lacking
(initial) values for the attributes in the utility function, since these links were previously unknown. For these links we proceed in the same manner as in the initialization of the choice process (see 6.12). Consider $p \in P$. We can distinguish two cases: all links in $p$ are in the newly known network, or there is at least one link in $p$ that is not present there.

**The case** $p \subseteq L(D'_{il})$: **the path is in the newly known network**

Based on individual knowledge expected travel time on $p$ is $T_{ipt} = \sum_{i \in p} T_{ilt}$. This expected travel time can be determined because all links in $p$ are known. Without information $i$, we would base his choices on $K_{il}$ and $E_{il}$. Suppose the message provides travel time $TT_{ipt}$.

Let us define the $f_{ipt}$ denoting the factor that the expected travel time of path $p$ has to be multiplied by to get $TT_{ipt}$. Thus $f_{ipt} = \frac{TT_{ipt}}{\sum_{i \in p} T_{ilt}}$. Now the expected travel times of all links in $p$ are multiplied by $f_{ipt}$. Further, for all links in $p$ the variance is set to 0. With these updated travel times and variances new link utilities are calculated.

One link may be present in more than one path. This would result in different factors for that link for each path in which the link is present. This problem may be solved by determining the mean factor for each link that is present in more than one path, and having determined this the other links are assigned a new factor to meet the contents of the messages. This whole concept can be described by the next procedure:

---

**Step 1** (Determine Path Factors)

\[
\forall p \in P: f_{ipt} \rightarrow \frac{TT_{ipt}}{T_{ipt}}
\]

if $\forall p \in P: f_{ipt} < 1 + \omega_3$ then STOP
Model Specification

Step 2 (Determine Link Factors and Apply)

\[ \forall l \in L(\lambda(P)) : \]
\[ \delta_{lp} \leftarrow \frac{\sum_{p \in P} f_{lp}}{\sum_{p \in P} \delta_{lp}} \]
where \( \delta_{lp} = 1 \) when \( l \in p \) and 0 otherwise

\[ u_{il} \leftarrow u_{il} \cdot f_{il} \]
\[ u_{ipt} \leftarrow \sum_{i \in p} u_{ipt} \]

GOTO step 1

This procedure is very similar to a method used in OD-matrix estimation according to information minimization (Van Zuylen & Willumsen, 1980). The procedure holds only if the message replaces expectations completely. This will only happen when the credibility of the information system is maximal, i.e. 1. When the credibility is not maximal and also differs per message, the procedure can be enhanced by introducing elastic constraints, with the credibility being the elasticity. Again the similarity with OD-matrix estimation is obvious, since here we adopt principles from the model developed by Hamerslag and Immers (1988).

Suppose at time \( t \) the credibility of the information is \( c_{it} \). (If \( i \) should be dealing with messages from more than one system, each message would have a perceived quality). The credibility is defined as a value between 0 and 1. Credibility is 0 when the information is perceived as so bad that the message is completely ignored. Credibility is 1 when the information is perceived as so good that the message is completely believed and the expectations of the individual will be completely replaced by the message.

Instead of using the elastic constraints with \( c_{it} \) being the elasticities we can also proceed as follows: for individual \( i \) the message with credibility \( c_{it} \) saying that travel time along known path \( p \) is \( TT_{ipt} \) equals the message with credibility 1 saying travel time along known path \( p \) is \( c_{it} TT_{ipt} + (1 - c_{it}) \sum_{i \in p} u_{ipt} \). The way to proceed with a message with credibility 1 was shown in the procedure listed above.

The case: \( p \not\in L(D_{ip}) \), the complete path is not in the newly known network

In this case not all links in \( p \) are known, \( \exists l \in p: l \not\in L(D_{ip}) \), so from his knowledge \( i \) cannot determine the expected travel time on \( p \). The message says \( TT_{ipt} \), but it cannot be compared with the knowledge. From this it follows that the message on \( p \) cannot be processed by \( i \) and it will be ignored. We give
an example:

So $L(D^{'}) = \{(o,1),(o,2),(1,2),(1,d),(2,d)\}; p = ((3,1),(1,2))$ thus $p \notin L(D^{'})$.
Thus a message about $p$ cannot be processed by $i$.

6.17 Prescriptive Information

Prescriptive information tells individuals what to do. According to the information system the best option is presented, for instance according to travel time. The information prescribes the use of paths $p$. It may be observed that the information on structure is not always known to $i$. For instance, if the information system is a route guidance system, it may provide the message 'Turn left' at an intersection. Some individuals have no knowledge of the implied path; they only know that according to the system, the best path between the intersection and his destination has as first link to the left at the intersection.

The contents of a prescriptive message is that the advised path is the best according to some measure of impedance. Individuals can either comply with the advice, or make their own choice. The level of compliance depends on the credibility of the information system. Compliance will therefore also depend on the history of experiences. E.g. drivers who were well advised by the prescriptive information system four times in a row, and who arrive late after complying with the advice a fifth time, are less inclined to consider the system lacking in credibility then drivers whose first experience with the system turns out badly. Also, the opposite holds.

To model these ideas a logarithmic buffer structure was defined. The size of the buffer reflects the number of bad experiences with the prescriptive information system compared to the number of good experiences a person will accept before compliance decreases. Generally this can be modelled as follows. Suppose the buffer at time $t$ for individual $i$ is $B_i = B_i(g_{it}, b_{it})$, with $b_{it}$ the number of bad experiences and $g_{it}$ the number of good experiences.

We define $B_i(g_{it}, b_{it}) = \max(0, \left\lfloor \frac{1}{2} \log(g_{it} + 1) \right\rfloor - b_{it})$. And in 6.14 it was already
defined that \( g_{it} = \sum_{\tau=1}^{t-1} \sum_{\rho} \sigma_{\tau} \delta_{i\rho\tau} \) and \( b_{it} = \sum_{\tau=1}^{t-1} \sum_{\rho} (1-\sigma_{\tau}) \delta_{i\rho\tau} \).

Now \( PC_{it} \), the compliance, initially is \( PC_{i1} \), and is updated according to the following rules:

- a bad experience follows after ignoring the prescriptive message
  \( PC_{it} \) becomes \( g(B_{i,t-1} \cdot f(g_{i,t-1})) \) and \( g_{it} = g_{i,t-1} + 1 \)
- good experience follows after ignoring the prescriptive message
  when \( B_{i,t-1} = 0 \), so when the buffer is empty, \( PC_{it} \) becomes \( g(B_{i,t-1}) \) and \( b_{it} = b_{i,t-1} + 1 \)
- a bad experience follows from compliance with the prescriptive message:
  when \( B_{i,t-1} = 0 \), so when the buffer is empty, \( PC_{it} \) becomes \( g(B_{i,t-1}) \) and \( b_{it} = b_{i,t-1} + 1 \)
- a good experience follows from compliance with the prescriptive message
  \( PC_{it} \) becomes \( g(B_{i,t-1} \cdot f(g_{i,t-1})) \) and \( g_{it} = g_{i,t-1} + 1 \)

With,

\[
\begin{align*}
  h(x) &= \min(\max(x,0), B_{\text{max}}) \\
  f(x) &= f_0 - h(x)/10 \\
  g(x) &= \min(x, PC_{it})
\end{align*}
\]

This algorithm concurs with the behavioral assumptions that were presented, but formal validation was not carried out. So only if the buffer is empty can the probability of compliance become less.

Thus it can be derived that when there is a prescriptive message that advises route \( r \) that

\[
P_{ir} = PC_{ir} + (1-PC_{ir}) (H_{ir} PIN_{ir} + (1-H_{ir}) PUM_{ir}) \quad (6.22)
\]

and when the message advises another route that

\[
P_{ir} = (1-PC_{ir}) (H_{ir} PIN_{ir} + (1-H_{ir}) PUM_{ir}) \quad (6.23)
\]

6.18 Credibility of Information

This section describes how the credibility of information is determined and how it may evolve over time. The credibility \( c_{it} \) that individual \( i \) assigns to the information at time \( t \) depends on all previous experiences with the information from the system. When an experience is bad, the credibility of information does not increase; when an experience is good, it does not decrease. Initially
the perceived quality of information is maximal, e.g. equal or close to 1. This means that initially people completely trust the information to be correct\(^3\).

| \( |TT_{ipt} - ett_{ipt}| \leq \omega_1 \) | good |
|---|---|
| \( |TT_{ipt} - ett_{ipt}| > \omega_1 \) | bad |
| \( ett_{ipt} - tt_{ipt} \leq \omega_2 \) | good |
| \( ett_{ipt} - tt_{ipt} > \omega_2 \) | bad |

Figure 6.9 Scheme for assessing the credibility of information

Suppose a descriptive message was about path \(p\), and the actual chosen route was \(r\). Two cases can be distinguished: \(p \subseteq r\) and \(p \not\subseteq r\).

When \(p \subseteq r\) it easy to determine whether the information was correct. When for instance the descriptive information was that the travel time along path \(p\) is \(TT_{ipt}\), and the experienced travel time is \(ett_{ipt}\), the experience is good if \( |TT_{ipt} - ett_{ipt}| \leq \omega_1 \), and bad if \( |TT_{ipt} - ett_{ipt}| > \omega_1 \). Again we adopt here a bounded rational assessment rule.

When \(p \not\subseteq r\), i.e. if \(p\) is not executed by \(i\), it is impossible to evaluate such a message.

\(^3\) For the credibility of an information system we assume the same principle as is present in our legal system, where any individual is assumed innocent until proven guilty.
When information is prescriptive, there is no equally obvious rule to distinguish between good and bad.

When \( p \subseteq r \) the experience is good when \( ett_{ipr} - \tau_{ipr} \leq \omega_2 \) and bad otherwise. Prescriptive information tells the individual that \( p \) is best, but since he cannot experience both \( p \) and an alternative \( p' \) for \( p \), the only judgement that can be made is whether \( p \) was a disappointment, i.e. when the experienced travel time along \( p \) was considerable longer than expected. When \( p \) was no disappointment, the experience was good, and the experience was bad otherwise.

When \( p \not\subseteq r \) and \( p \) is an \((n_1, n_2)\)-path an assessment of the quality of this information can be made only when both \( n_1 \) and \( n_2 \) are on the chosen route \( r \), in other words, when there exists an alternative \((n_1, n_2)\)-path \( p' \) in \( r \). When \( ett_{ip'1} - \tau_{ip'1} < \omega_2 \) the experience with the information system is bad, since the alternative path did not result in a disappointing travel time. When the opposite holds, so when the experience with \( p' \) was disappointing, the experience with the information system is good.

We can conclude the assessment of the quality of a message with structure \( p \), an \((n_1, n_2)\)-path with the scheme as depicted in Figure 6.9.

6.19 Departure Time Choice

Thus far departure time choice has not been addressed. In this section this choice process is discussed, together with its relation to the route choice process. In the end it will turn out that no obvious difference exists between the two processes, and that they will be merged into one pseudo-simultaneous process.

In the choice of departure time we will follow the approach via arrival time choice. Once an arrival time has been chosen the departure time follows immediately by subtracting the expected travel time. There is no apparent reason for this, other than it is a choice between departure time choice or arrival time choice, and one needs to be chosen. Only schedule delay can be determined more directly following the arrival time choice approach.

Contrary to route choice, arrival time choice is a non-discrete choice process. There exist an infinite number of choice alternatives. Since it is inconceivable that any individual is capable of dealing with this infinite number of choice alternatives and also for computational reasons the choice process will be reformulated as being discrete.

For any individual \( i \) that plans to travel on day \( t \) from an origin \( o \) to a destination \( d \) a so-called preferred arrival-time \( pat_i \) has to be assumed. For a home-to-work trip this may be the starting time of the company. Obviously when \( i \) is choosing another arrival time than \( pat_i \) he has to deal with either coming too early or too late. This will be called schedule delay. Around \( pat_i \) an arrival time interval will be constructed which will be divided into \( nt \) sub-
intervals each with midpoint $at_{ikk}$. The choice process now becomes discrete when stating that the alternatives are the arrival times $at_{ikk}$. At this point we can refer to the route choice process where also a discrete number of alternatives did exist. Similarly to the route choice process in an environment without information an arrival time can be chosen out of habit or since it has the highest expected utility. The habit-branch in the route choice-process is completely transferable to this process. The expected utility maximization however becomes slightly different.

In defining the utility function for the $k$th arrival time interval we observe that the utility consists of two parts: the first part being the utility that results from the chosen route and the second part that relates to schedule delay. This already implies that for each interval the route choice process must be executed, so as to determine the utility that is associated with the chosen route. Now suppose that for interval $k$ route $r$ is chosen then the expected utility $W'_{ikk}$ becomes:

$$W'_{ikk} = \alpha_1 \text{early}_{ikk} + \alpha_2 \text{late}_{ikk} + \alpha_3 \text{late}^2_{ikk} + \alpha_4 V_{irr}^k$$

(6.24)

where $\text{early}_{ikk}$ amount of time that $i$ is early as a result of arrival time interval $k$, so $\text{early}_{ikk} = \max(0, at_{ikk} - at_{ik})$

$\text{late}_{ikk}$ amount of time that $i$ is late as a result of arrival time interval $k$, so $\text{early}_{ikk} = \max(0, at_{ik} - pat_{ir})$

$V_{irr}^k$ expected utility resulting from route $r$ in interval $k$ according to (6.6)

$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ parameters

The square of $\text{late}_{ikk}$ is added to ensure that once someone is very late, an extra couple of minutes do not really matter (Hendrickson & Planck, 1984). Adding an error term which is independently Gumbel distributed results in a logit model.

Suppose that for each interval $k$, $i$ has an expected utility of route $r$, $V_{irr}^k$ and suppose further that the utility maximization part of the route choice model is also logit.

For interval $k$ the probability of choosing route $r$ can be denoted as:

$$P_{irr}^k = (1 - H_{ir}) \frac{\exp(V_{irr}^k)}{\sum_{\rho} \exp(V_{irr}^{\rho})} + H_{ir} PIN_{irr}$$

(6.25)

Suppose in interval $k$ route $r_k$ is chosen, Thus for interval $k$ the utility becomes $W'_{ik}$. In this case the probability that interval $k$ is chosen is:

Thus the overall probability of choosing interval $k$ from utility maximization
\[
\Pr(\text{interval } k \text{ is chosen}) = \frac{\exp(W_{ikr}^r)}{\sum_l \exp(W_{ilr}^r)}
\]  
(6.26)

becomes:

\[
\Pr(\text{interval } k \text{ is chosen}) = \sum_{r_1} \ldots \sum_{r_m} \left( \prod_k P_{ir_t}^k \frac{\exp(W_{ikr}^r)}{\sum_l \exp(W_{ilr}^r)} \right)
\]  
(6.27)

Note that this formulation implies a simultaneous decision process. This is more realistic than the conditional way of modelling where for instance first a departure time and then a route conditional to the departure time is chosen.

Let us denote the probability that interval \( k \) is chosen from habit as \( HH_{il} PP_{ik}^{\text{in}} \) where \( HH_{il} \) is the total habit strength for arrival time choice, then the total probability that interval \( k \) is chosen becomes:

\[
PP_{ikr} = (1 - HH_{il}) \left[ \sum_{r_1} \ldots \sum_{r_m} \left( \prod_k P_{ir_t}^k \frac{\exp(W_{ikr}^r)}{\sum_l \exp(W_{ilr}^r)} \right) \right] + HH_{il} PP_{ik}^{\text{in}}
\]  
(6.28)

Update procedures

In the preceding paragraphs it was shown that arrival time choice has basically the same properties as route choice. As said before the habit part in this process is the same as in the route choice process. Of more interest is the utility maximization part.

In order to determine \( W_{ikr}(r) \) the individual makes use of his experiences. Suppose for reasons of simplicity that the utility function for route choice consists only of expected travel time. Since for each interval an utility is determined, for each interval an expected travel time must be determined too. Now an experience is an experienced travel time for a route-interval combination. Thus similar to (6.7) the update procedure becomes

\[
tt_{il}^k = \delta_{il,t-1} + \Psi tt_{il,t-1}^k + (1 - \Psi) ett_{il,t-1} + (1 - \delta_{il,t-1})tt_{il,t-1}
\]  
(6.29)

with

\[
tt_{il}^k \quad \text{the expected travel time for link } l \text{ for interval } k
\]
\[
\delta_{il}^k \quad \text{parameter, } 1 \text{ when link } l \text{ was chosen for interval } k \text{ and } 0 \text{ otherwise}
\]
\[
\Psi \quad \text{learning-parameter}
\]
Arrival time choice and information

The way in which information was used in route choice can be directly transferred to the arrival time process. Descriptive information will be used in the utility function, and prescriptive information is either followed or not.

This is the big advantage of having built a model structure that combines route and arrival time choice as was depicted in (6.24).

Determination of departure time

Suppose interval $k$ was chosen and route $r$, then obviously the departure time becomes $at_k - t_{ir}^k$.

6.20 Loading

Running the algorithms as discussed in this chapter so far yields at day $t$ for each individual $i$ a planned trip $PT_{ir}$. Each planned trip has a planned departure time $DT_{ir}$ and a planned route $R_{ir}$. We define $PT_i$ as the set of all planned trips for day $t$. Further $PT_{ir}$ can be denoted as the tupel $(DT_{ir}, R_{ir})$. The assumption in the model is that when $i$ does not receive any further information the trip will be executed as planned. In this section the loading algorithm for execution is presented.

First we define the function $\omega_{DT}$ that defines an ordering with $DT$ as key. Thus it holds that $\omega_{DT}(PT_i) = (PT_{i,1}, PT_{i,2}, \ldots)$ such that $PT_i \ominus \omega_{DT}(PT_i) = \emptyset$ and $DT_{ir} \leq DT_{i,r} \forall k \geq 1$. Without loss of generality we may assume that $\omega_{DT}(PT_i) = (PT_{i,1}, PT_{i,2}, \ldots)$.

Also we define for each planned trip $c_{ir}$ being the state of the planned trip of individual $i$ at day $t$ at time $\tau$. The state can be denoted as a 3-tupel $c_{ir} = (l_{ir}, d_{ir}, r_{ir})$, where $l_{ir}$ is the link where individual $i$ is at time $\tau$, $d_{ir}$ is the departure time from the head of $l_{ir}$, and $r_{ir}$ is the planned route starting at the head of $l_{ir}$. Initially it holds that $l_{i0} = \emptyset$, $d_{i0} = DT_{ir}$ and $r_{i0} = R_{ir}$.

As defined before, any route is an ordered set of links. We define further the function $\Phi(r_{ir})$ as the index of the first link of $r_{ir}$, so $\forall r = (l_k, \ldots)$ $\Phi(r) = k$. For each link $l$ in the network a speed-density function $\lambda_l(\rho) = \nu$, with $\rho$ is the density and $\nu$ is the speed, and a length $\lambda_l$ were defined. Since traffic conditions on each link are assumed to be homogeneous the time spent on link $l$ with density $\rho$ is $\tau_l(\rho) = \frac{\lambda_l}{\lambda_l(\rho)}$. The loading mechanism can now be defined as follows:
Step 1  (Initialization)
for all links in the network density is set to 0, so \( \forall l \in L(D) \rho_l \leftarrow 0 \)
\( \tau \leftarrow 0 \)
define initial states for all individuals \( i \) \( l_{ir} \leftarrow \emptyset \), \( dt_{ir} \leftarrow DT_{it} \), \( r_{ir} \leftarrow R_{it} \)
sort the set of states: \( \xi_{ir} = \omega_{ir} \{ \xi_{1ir}, \xi_{2ir}, \ldots \} \)

Step 2  (Move car)
let time run until first car departs, so perform \( \xi_{ir+1} \leftarrow \xi_{ir} \) and \( \tau \leftarrow \tau + 1 \) until
\( \tau = d_t^{l_{(c_{ir})}} \)
suppose \( i \) is first individual so \( k \leftarrow \Phi(r_{ir}) \)
\( \tau_{ir} \leftarrow \frac{\lambda \lambda_i}{\hat{y}_i(\rho_i)} \) and \( dt_{ir} \leftarrow dt_{ir} + \tau_{ir} \), so traveltime on \( l_k \) is determined and
departure time is updated
\( \rho_i \leftarrow \frac{\rho_i \lambda \lambda_i + 1}{\lambda \lambda_i} \) and \( \rho_i \leftarrow \frac{\rho_i \lambda \lambda_i - 1}{\lambda \lambda_i} \) with \( l \) is previous link so density of new
link and previous link are updated
\( r_{ir} \leftarrow r_{ir} - l_k \)
\( l_{ir} \leftarrow \Phi(r_{ir}) \)
if \( r_{ir} = \emptyset \) then \( \xi_{ir} = \xi_{ir} - \xi_{ir} \)
\( \xi_{ir} = \omega_{ir}(\xi_{ir}) \)

Step 3  (Stop-criterium)
if \( \xi_{ir} = \emptyset \) then STOP else GOTO Step 2.

This procedure can also be applied when, during the performance of the trip, information is received and the original plans are altered because of this. Suppose a traveller \( i \) is at time \( \tau \) in state \( \xi_{ir} = (l_{ir}, dt_{ir}, r_{ir}) \). The planned route is \( r_{ir} \).
Suppose that using the information provided the planned route is altered into \( r'_{ir} \), than the state of \( i \) will alter to \( \xi_{ir} = (l_{ir}, dt_{ir}, r'_{ir}) \). The way to determine a route using the information given is the same as that defined in the previous sections, only now the origin of the trip becomes the head of \( l_{ir} \). The route that will be recorded as the one that was executed is \( r_{i0} \) until \( l_{ir} \), followed by \( r'_{ir} \).
Tests and Validation: Descriptive Information

7.1 Introduction

In this chapter a study is presented to test and validate the route choice model. Contrary to the study in Chapter 8 which tests the model in a situation with prescriptive information, this study tests the model for a situation in which descriptive information is provided to drivers. One of the main problems encountered was that since our model is different from existing choice models, no procedure existed to estimate the model parameters simultaneously. As a result a new estimation procedure was developed. This procedure makes it possible to estimate the model parameters simultaneously.

The aims of the present study are to estimate model parameter values of the utility maximization and habit rules, and to investigate whether parameter estimates change after descriptive information is provided to the travellers. The study also aims to show what the effects of descriptive information are in terms of experienced congestion.

For the investigation data from a longitudinal panel study were used. This panel study was part of a large scale study carried out to determine the impact of a variable message sign showing dynamic queue length information. This study was reported by BGC (1992, 1993) to Rijkswaterstaat Noord-Holland and the Transportation and Traffic Research Division.

There are four main characteristics of this study: travellers are familiar with the route alternatives, the data were collected in a field-study, drivers were provided with descriptive information, and data were collected for a number of consecutive choices.

This chapter has the following structure. Section 7.2 describes the location of the variable message sign. Section 7.3 discusses the longitudinal panel study to collect the data. The subsets of data used for the present study are discussed in detail. Section 7.4 presents the actual model that was estimated and used
to simulate the panel data. Section 7.5 deals with the initial values. Section 7.6 presents a newly developed likelihood estimation method to simultaneously estimate model parameters. In Section 7.7 model parameter estimates, model fit, and results on the effect of descriptive information on experienced congestion are presented. Finally, in Section 7.8 the results of the study are discussed.

7.2 The RIA variable message sign

The motorway system around the city of Amsterdam involves the ringway A10, and six connecting motorways. The city is connected to the ringway by a radial system of arterials. Two tunnels are part of the ringway, the Coentunnel and Zeeburgertunnel. During the morning peak, when traffic is oriented towards the city, the Coentunnel is usually congested.

Figure 7.1 Highway system around Amsterdam including the Coentunnel and Zeeburgertunnel
On November 14th 1991 a variable message sign, which was named the RIA-sign (Route Information Amsterdam), was installed on motorway A8 (Figure 7.1, see also Figure 2.1). The sign is the first of the proposed RIA-system which is a series of signs, aimed to provide route information about the complete ringway A10.

The first RIA-sign provides travellers with information about congestion before the two tunnels on the A10. The sign provides queue information, i.e. the physical length (in kilometers) of queues before the Coentunnel and/or Zeeburgertunnel, or about obstruction of the tunnels. When congestion is absent, the sign shows the names of both tunnels with directional arrows. This information is generated automatically from MCSS\(^1\)-data.

The goal of the sign is to inform road users approaching Amsterdam from the North via motorway A8 in such a way that they can decide whether the ringway A10-North (direction Zeeburgertunnel) or A10-West (direction Coentunnel) is the best route to their destination.

### 7.3 The Panel Study

To learn about the effects of the RIA-sign on the route choice of individual road users over time, a longitudinal panel study was set up. The panel study investigated route choice behaviour of a group of car drivers over four waves (one before and three after introduction of the RIA-sign, see Table 7.1). Each wave consisted of 15 workdays. Only car drivers who entered the ringway via motorway A8 at least three times weekly during the morning peak were selected for the panel.

<table>
<thead>
<tr>
<th>wave</th>
<th>period</th>
<th>participants</th>
<th>trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (before study)</td>
<td>27.10.91 - 15.11.91</td>
<td>458</td>
<td>5,380</td>
</tr>
<tr>
<td>2 (1st post study)</td>
<td>17.11.91 - 6.12.91</td>
<td>439</td>
<td>4,787</td>
</tr>
<tr>
<td>3 (2nd post study)</td>
<td>10.2.92 - 27.2.92</td>
<td>334</td>
<td>3,908</td>
</tr>
<tr>
<td>4 (3rd post study)</td>
<td>4.5.92 - 22.5.92</td>
<td>288</td>
<td>3,037</td>
</tr>
</tbody>
</table>

In each wave the panel members were asked to record the following for each trip on the ringway in a travel diary:
- destination;

\(^1\) Motorway Control and Signalling System (see Rijkwaterstaat, 1992).
- departure time;
- arrival time at the RIA sign;
- arrival time at destination;
- chosen route;
- observed RIA information and
- experienced congestion.

During the first wave the RIA-sign was not yet operating. RIA-messages (i.e. queue lengths at the tunnels) were simulated for the morning peak period from MCSS data.

**Data**

For each wave the combination of individual, destination (postal code) and period (peak or off-peak) defines a maximum series of 15 consecutive route choices. Each series is treated as a distinct 'individual'. A series for individual $i$, destination $d$ and period $p$ is only analyzed when there is at least one individual who reached destination $d$ in period $p$ through the Coentunnel and there is also at least one individual who reached $d$ in $p$ through the Zeeburgertunnel. Only 'individuals' (i.e. a combination of individual, destination and period) who (also) participated in the first wave were analyzed. From Section 7.4 on a combination of individual, destination and period that meets the requirements for analysis purposes will be referred to as an individual.

**Table 7.2 Data for all waves**

<table>
<thead>
<tr>
<th>wave</th>
<th>panel size</th>
<th>analyzed panel</th>
<th>'individuals' analyzed</th>
<th>trips analyzed</th>
<th>trips / 'individual'</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>458</td>
<td>290</td>
<td>352</td>
<td>3,042</td>
<td>7.64</td>
</tr>
<tr>
<td>2</td>
<td>439</td>
<td>237</td>
<td>254</td>
<td>2,366</td>
<td>9.32</td>
</tr>
<tr>
<td>3</td>
<td>334</td>
<td>155</td>
<td>163</td>
<td>1,597</td>
<td>9.80</td>
</tr>
<tr>
<td>4</td>
<td>288</td>
<td>125</td>
<td>130</td>
<td>1,158</td>
<td>7.91</td>
</tr>
</tbody>
</table>

In wave 1 trips from 290 out of 458 panel participants met the requirements for analysis. From these 290 panel members 352 'individuals' were constructed. In total 3,042 trips were analyzed for wave 1, which equals 7.64 trips per 'individual'. Statistics for all waves are listed in Table 7.2.

Average year kilometrage of analyzed panel members was 32,000 km, mean age was 42 years.

Though there was considerable drop out of participants and even larger drop out of 'individuals' over waves, this drop out did not influence the results of the study. To test effects of drop out, analyses for wave 1 were also carried
out only for those participants who remained in wave 4. These results did not
differ from results for the complete wave 1 dataset.

In all four waves no accidents occurred.

7.4 Model Specification

The same model as presented in Chapter 6 was used, though with a few
relaxations.

First, assessment and updating of the perceived quality (credibility) of the
information system was not integrated. For all trips panel members were asked
to judge whether their route choice had been correct and whether they judged
the RIA information to be correct. Only a very small fraction of drivers judged
their route choice and the RIA-information incorrect (wave 2 0.5%; wave 3
0.4%; wave 4 0.2%). It thus seems that drivers found the information very
credible. To generalize this finding perceived quality of the information system
was assumed 1 for each individual on each day, so \( c_{it} = 1 \quad \forall \quad i, t \).

Second, the dependency between habit updates and the evaluation as to whether
the experienced travel time is larger or smaller than expected (see Section 6.14),
was excluded from the model, thus \( \alpha_{it} = 1 \quad \forall \quad i, t \). This decision simplifies the
model somewhat. For the present study we feel this step is justifiable, because it
diminished computational effort to estimate the model which was done on
a standard 386 PC.

Third, the algorithm to determine the known routes (see Section 6.12) is
not included in the present model specification. For the present study only two
routes from the RIA-sign to the destination are assumed known. We focus on
the binary choice situation under the RIA-sign, and do not deal with route choice
after turning right or left in the direction of one of the tunnels. Considering
the circumstances and the familiarity of all drivers with the choice situation,
it seems plausible that all drivers know both routes.

With these relaxations in mind, for each wave \( w \) the model (see (6.11)) may
be reformulated as\(^2\):

\[
P_{irt} = H_{it} PIN_{irt} + (1 - H_{it}) PUM_{irt} \tag{7.1}
\]

with

- \( P_{irt} \) the probability that individual \( i \) chooses route \( r \) on day \( t \)
- \( PIN_{irt} \) the probability that individual \( i \) chooses route \( r \) on day \( t \) because of
  habit

\(^2\) If not indicated otherwise formulas are valid \( \forall i, r \) and \( 15.(w-1) + 1 \leq t \leq 15.w \)
$PUM_{irt}$ the probability that individual $i$ chooses route $r$ on day $t$ because of highest (perceived) expected utility

$H_{it}$ the habit strength for individual $i$ on day $t$

Days are numbered 1 to 15 in wave 1, 16 to 30 in wave 2 etc.

Before we go into more detail we define

$$\delta_{irt} = \begin{cases} 
1 & \text{if individual } i \text{ chooses route } r \text{ on day } t \\
0 & \text{otherwise}
\end{cases}$$ (7.2)

and

$$\Delta_{irt}^w = \sum_{r=(w-1)15+1}^t \delta_{irt}$$ (7.3)

$$\Delta_{it}^{wr} = \sum_r \Delta_{irt}^w$$ (7.4)

$$\delta_{it}^r = \sum_r \delta_{irt}$$ (7.5)

Thus

$\Delta_{irt}^w$ number of times individual $i$ has chosen route $r$ from the first until the $t^{th}$ day in wave $w$

$\Delta_{it}^{wr}$ number of times individual $i$ has chosen a route from the first until the $t^{th}$ day in wave $w$

$\delta_{it}^r$ number of routes chosen by individual $i$ at day $t$

In Chapter 6 habit strength was defined (see (6.21)). In this context this formula becomes

$$H_{it} = H_{\max} (1 - \exp(-\alpha \sum_{w=1}^{[t/15]+1} \Delta_{it}^{wr}) \forall t \geq 2$$ (7.6)

For the present study this definition may be simplified. All drivers in the study were regular commuters, who have encountered the choice situation many times. Therefore, it seems plausible to assume maximum habit strength throughout all waves. In other words,

$H_{it} = H_{\max}$ is assumed. Thus (7.6) becomes

$$H_{it} = H_{\max} = H$$ (7.7)

This implies that it is not necessary to estimate parameter $\alpha$, that models the speed in which habit strength is build up. Substitution of (7.7) in (7.1) yields

$$P_{irt} = H \cdot PIN_{irt} + (1 - H) \cdot PUM_{irt}$$ (7.8)

The dynamic formulations for the probability that a route choice is based on habit and for the probability that a route choice is based on utility maximization
are the same as defined in Chapter 6 (see (6.17) and (6.20)). Now with \( \sigma_i = 1 \)
\( \forall i, t \), and assuming a logit formulation for the utility maximization part these formulas become

\[
PIN_{irt} = \frac{\gamma PIN_{ir,t-1} + \delta_{ir,t-1}}{\gamma + \delta_{ir,t-1}} \quad (7.9)
\]

\[
PUM_{irt} = \frac{e^{V_{ir}}}{\sum_{\rho} e^{V_{ir}}} \quad (7.10)
\]

with \( V_{irt} \) the expected utility for individual \( i \) on day \( t \) for route \( r \). Now the utility function has to be defined. Next to expected travel time and standard deviation of expected travel time, expected queue length must be incorporated as a utility component. Here instead of variance in travel time standard deviation is included in the utility function. The reason for this is that in some stochastic assignment models a weight is given to standard deviation. In this study we want to examine how this weight changes in an information environment.

When no information is provided the following utility function is assumed

\[
V_{irt} = \beta_1 T_{irt} + \beta_2 S_{irt} + \beta_3 f_{irt} \quad (7.11)
\]

with

- \( T_{irt} \) expected travel time by individual \( i \) for route \( r \) on day \( t \)
- \( S_{irt} \) expected standard deviation of travel time
- \( f_{irt} \) expected queue length
- \( \beta_1, \beta_2, \beta_3 \) utility parameters

The dynamic formulation of expected travel time is the same as defined in Chapter 6 (see (6.7))

\[
T_{irt} = \delta_{ir,t-1} (\psi T_{ir,t-1} + (1-\psi) ett_{irt}) + (1 - \delta_{ir,t-1}) T_{ir,t-1} \quad (7.12)
\]

with

- \( ett_{irt} \) experienced travel time
- \( \psi \) learning parameter

The dynamic formulation of expected queue length is defined in a similar way

\[
f_{irt} = \delta_{ir,t-1} (\psi f_{ir,t-1} + (1-\psi) ef_{irt}) + (1 - \delta_{ir,t-1}) f_{ir,t-1} \quad (7.13)
\]

with

- \( ef_{irt} \) experienced queue length
- \( \psi \) learning parameter
The dynamic formulation of the expected standard deviation in travel time is (see (6.10))

$$s_{ir} = \delta_{ir,r-1} \left[ \frac{t-3}{t-2} s_{ir,r-1}^2 + \frac{(ett_{ir,r-1} - t_{ir,r-1})^2}{t-2} \right] + (1 - \delta_{ir,r-1}) s_{ir,r-1}^2 \right]^{1/2} \quad (7.14)$$

When information is provided, the utility function becomes slightly different. In that case internal descriptive information processing is assumed, which means that expected queue length \( f_{ir} \) is replaced by the queue length according to the RIA sign \( ria_{ir} \).

It is further assumed that drivers who are provided with queue information, adjust their expected travel times accordingly. Suppose a driver expects a travel time of 15 minutes and no congestion. The RIA-sign informs him of a queue of 4 km on his route. It is likely that the driver will adjust his expected travel time with this information. To model this, the expected travel time \( t_{ir} \) is updated with the information \( ria_{ir} \) yielding \( t'_{ir} \) (7.15).

$$t'_{ir} = t_{ir} + \phi(ria_{ir} - f_{ir}) \quad (7.15)$$

with

\( \phi \) correction parameter for expected travel time using queue length information

\( ria_{ir} \) queue length on RIA-sign

Thus, when information is provided the utility function becomes

$$V_{ir} = \beta_1 t'_{ir} + \beta_2 s_{ir} + \beta_3 ria_{ir} \quad (7.16)$$

For the rest, the model stays the same, with the obvious observation that experienced queue length equals the information about queue length for a chosen route, thus

$$ef_{ir} = \sum_r \delta_{ir} ria_{ir} \quad (7.17)$$
7.5 Initial values

The dynamic formulations of $PIN_{ir}$, $tt_{ir}$, $f_{ir}$ and $s_{ir}$ require initial values for each wave. For the present study initial values had to be determined separately for each individual. Since, drivers in the study were regular commuters it may be assumed that initial values correspond with the actual choice behaviour and route performance during wave 1.

**Probability of habit**

During the first wave no information was provided. The choice behaviour during this wave was assumed to be the same as prior to this wave. For each individual (this time irrespective of destination and period) and route, $PP_{ir}$ was determined, denoting the proportion of choices route $r$ was used during wave 1. Thus

$$PP_{ir} = \frac{\Delta_{ir,15}}{\Delta_{15}}$$ (7.18)

It was assumed that the fraction of route $r$ choices by individual $i$ just before wave 1 is $PP_{ir}$. It was assumed further that the initial probability of habit of individual $i$ for route $r$ for wave 1 is more extreme than $PP_{ir}$. The reason for this assumption is that generally, the drivers in the study were very stable in their route choice behaviour. In those cases were $0.1 < PP_{ir} < 0.9$ almost always $PP_{ir}$ was based on a relatively small number of choices. We feel that it is likely that the route with the highest proportion $PP_{ir}$, was actually chosen more often in the period previous to wave 1 than $PP_{ir}$ indicates. Therefore, the initial probability of habit $PIN_{ir}$ was set to an (arbitrary) high value (0.9) for the favorite route. Obviously when the proportion is 0.5 no favorite route can be determined, so in that case $PIN_{ir}$ was set to 0.5. Thus,

$$PIN_{ir} = \begin{cases} PP_{ir} & \text{when } PP_{ir} \geq 0.9 \\ 0.9 & \text{when } 0.5 < PP_{ir} < 0.9 \\ 0.5 & \text{when } PP_{ir} = 0.5 \\ 0.1 & \text{when } 0.1 < PP_{ir} < 0.5 \\ PP_{ir} & \text{when } PP_{ir} \leq 0.1 \end{cases}$$ (7.19)

Since wave 2 immediately follows wave 1, the initial value for wave 2 were determined by

$$PIN_{ir,16} = \frac{\gamma PIN_{ir,15} + \delta_{ir,15}}{\gamma + \delta_{ir,15}}$$ (7.20)

Unfortunately there is a time gap between waves 2, 3 and 4. We have no data on choice behaviour or experiences during these gaps. To arrive at initial values for the beginning of these waves, we simply pretend that these gaps
do not exist. In this way, the definition of initial values for wave 2 also hold for wave 3 and 4.

Attributes of the utility function

It might be argued that experiences with both routes during the waves of the panel study make up a representative sample of experiences prior to wave 1. In those cases in which an individual has used both routes this allows us to calculate the initially expected travel times for both routes. Since some drivers did not switch between routes at all, initially expected travel time for the route that was not chosen had to be determined in another way. One of the data requirements (Section 7.2) allows for this. Because choice series for individual \( i \), destination \( d \) and period \( p \) are only analyzed when there is at least one individual who reached destination \( d \) in period \( p \) through the Coentunnel and also at least one individual who reached \( d \) in \( p \) through the Zeeburgertunnel, a measured travel time for both routes is always present in the dataset. Initial values for expected travel time, expected queue length and expected standard deviation in travel time were defined as follows:

For each individual \( i \) the set of individuals with the same destination and period \( I_i \) is defined. Obviously it holds that \( i \in I_i \). The data requirement from Section 7.2 means that

\[
\sum_{j \in I_i} \sum_{w=1}^{4} \Delta_{j,15}^{wr} \geq 1 \quad (7.21)
\]

For initial values we will use the mean. This is an arbitrary choice. It could be that we would have to use a weighted mean, but there is no indication what in that case these weights would be. We define initial values for expected travel time for wave 1 as

\[
U_{ir1} = \frac{1}{4} \sum_{j \in I_i} \sum_{\tau=1}^{60} \Delta_{j,15}^{wr} \sum_{j \in I_i} \sum_{\tau=1}^{60} \delta_{j,\tau} e_t_{j,\tau} \quad (7.22)
\]

Similarly, initial values for expected standard deviation of travel time as

\[
S_{ir1} = \left[ \frac{1}{4} \sum_{j \in I_i} \sum_{\tau=1}^{60} \Delta_{j,15}^{wr} \sum_{j \in I_i} \sum_{\tau=1}^{60} \delta_{j,\tau} (U_{ir1} - e_t_{j,\tau})^2 \right]^{1/2} \quad (7.23)
\]

and initial values for expected queue length as

\[
f_{ir1} = \frac{1}{4} \sum_{j \in I_i} \sum_{\tau=1}^{60} \Delta_{j,15}^{wr} \sum_{j \in I_i} \sum_{\tau=1}^{60} \delta_{j,\tau} f_{j,\tau} \quad (7.24)
\]
Similarly to the case of probabilities of habit we further assume all waves to be adjacent. For the initial values this means that initial value for wave \( w \) is the last value of wave \( w-1 \).

### 7.6 Estimation procedure

Because available estimation procedures are not suited to estimate the relevant model parameters simultaneously, for this study a new procedure, based on maximum likelihood, was developed. In this section a brief outline of the estimation procedure is presented. The procedure is presented in detail in Appendix A.

For the present study the relevant model parameters are \( H, \gamma, \psi, \beta_1, \beta_2 \) and \( \beta_3 \). These parameters were estimated from the following data for each wave \( w \):

- \( \Delta_w = \{ \delta_{irt} \} \) containing the actual route choice information
- \( ETT_w = \{ ett_{irt} | \delta_{irt} = 1 \} \) containing all experienced travel times
- \( EF_w = \{ ef_{irt} | \delta_{irt} = 1 \} \) containing all experienced queue lengths and
- \( RIA_w = \{ ria_{irt} | \delta_{irt} = 1 \} \) containing all RIA messages (for wave 1 these are simulated messages)

Since we are interested in whether and how much the values of parameters change over time as a consequence of the information provided to the drivers, estimation was carried out for each wave separately. For wave \( w \) the log-likelihood function can be derived as

\[
\mathcal{L}_w = \sum_i \sum_{r=\{w-1\}+1}^{w+15} \log \left( \prod_r (1 - \delta_{irt}) + \sum_r \delta_{irt} P_{irt} \right) \quad (7.25)
\]

The term \( \prod_r (1 - \delta_{irt}) \) is added to make sure that on days where \( i \) did not choose a route there is no contribution to the likelihood. Necessary conditions for maximizing \( \mathcal{L}_w \) (Luenburger, 1984) are:

\[
\begin{align*}
\frac{\partial \mathcal{L}_w}{\partial H} &= 0, & \frac{\partial \mathcal{L}_w}{\partial \gamma} &= 0, & \frac{\partial \mathcal{L}_w}{\partial \psi} &= 0, \\
\frac{\partial \mathcal{L}_w}{\partial \beta_1} &= 0, & \frac{\partial \mathcal{L}_w}{\partial \beta_2} &= 0, & \frac{\partial \mathcal{L}_w}{\partial \beta_3} &= 0. 
\end{align*}
\quad (7.26)
\]

Parameters \( H, \gamma, \psi, \beta_1, \beta_2 \) and \( \beta_3 \) were estimated for all waves using the developed likelihood estimation procedure. It is not necessary to estimate the factor \( \phi \), which corrects expected travel time for queue information (see (7.16)) with this procedure.
7.7 Results

Parameter estimates

For the model in which descriptive information is processed (wave 2 to 4), the factor $\phi$ that updates expected travel time using queue length information, was determined as follows. For $\psi = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.99$ expected travel times and queue lengths were computed according to (7.12) and (7.16) for wave 2 to 4 for different values of $\phi$. This yielded a list of expected travel times dependent on $\psi$ and $\phi$. Regressing expected travel times on experienced travel times and corrected expected travel times, showed that for all tested values of $\psi$ the best value for $\phi$ is 0.0125. This means that 'optimal' travel time expectations were reached by adding 0.0125 hours to the originally expected travel time for each kilometer that queue length was underestimated.

The results of the maximum likelihood estimation for all waves are listed in Table 7.3. The upper part of the table shows the estimated values of the parameters of the model. The lower part shows summary statistics to demonstrate the model goodness of fit (see Ben-Akiva and Lerman, 1985).

Table 7.3 Estimated parameters for all waves

<table>
<thead>
<tr>
<th>parameters</th>
<th>wave 1 (n=3,042)</th>
<th>wave 2 (n=2,366)</th>
<th>wave 3 (n=1,597)</th>
<th>wave 4 (n=1,158)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H$</td>
<td>0.99</td>
<td>0.90</td>
<td>0.89</td>
<td>0.88</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>159</td>
<td>159</td>
<td>159</td>
<td>159</td>
</tr>
<tr>
<td>$\psi$</td>
<td>0.99</td>
<td>0.89</td>
<td>0.87</td>
<td>0.67</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>-90</td>
<td>-90</td>
<td>-90</td>
<td>-80</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-107</td>
<td>-50</td>
<td>-50</td>
<td>-25</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-1.95</td>
<td>-2.22</td>
<td>-3.35</td>
<td>-6.75</td>
</tr>
</tbody>
</table>

summary statistics

| $\mathcal{L}(c)$ | -2 031.4 | -1 617.6 | -1 083.6 | -786.3 |
| $\mathcal{L}(x^*)$ | -359.4 | -377.4 | -237.9 | -213.4 |
| $\rho^2 = 1 - \frac{\mathcal{L}(x^*)}{\mathcal{L}(c)}$ | 0.82 | 0.77 | 0.78 | 0.73 |

From the inspection of the values of $\rho^2$ (analogous to $R^2$ in regression) it may be concluded that the model fits well for all waves: $\rho^2$ is 0.82, 0.77, 0.78 and 0.73 for wave 1 through 4.
Interpretation of the upper part of the table shows that during the first wave choice behaviour is almost completely dominated by habit ($H=0.99$). For the next waves $H$ decreases, though it still dominates choice behaviour. In wave 2, 3 and 4 the decrease of $H$ is respectively 8%, 11% and 12% compared to wave 1. This means that utility maximization plays only a modest role in the choice behaviour at hand.

The distribution of habit strength over the two routes is stable over waves. The magnitude 159.1 of $\gamma$ indicates that this distribution changes only slowly, that is, after quite a large number of choices. The stability of $\gamma$ over waves might further indicate that changes in this distribution are rather independent of other model parameters.

The weight given to the most recent experience in the learning process, denoted by $(1-\psi)$, increases over waves. After introducing information the weight given to the most recent experience in the learning process increases (in wave 2, 3 and 4 the weight given to the most recent experience increases with 11%, 13% and 33% compared to wave 1). In fact, during wave 1, if drivers are not choosing habitually, they seem to rely almost completely on general expectations about utility attributes which were built up over a longer time period. This finding could be considered to be a normal description of an equilibrium situation. In such situations drivers would not respond much to day-to-day variations in travel time, because these variations are experienced as incidents. It is interesting to note that when utility maximization as a choice rule gains in importance, the most recent experience also gains importance in the learning process. It looks as if utility maximization occurs more frequently in non-equilibrium than in equilibrium situations.

Three parameters of the utility function were estimated. The weight given to expected travel time in the utility function ($\beta_1$), is stable over the first three waves. This is what would be expected since travel time is considered the major criterion in trade-offs between routes. There is no reason to expect any change in this parameter. Unfortunately, $\beta_1$ decreases from -90 to -80 from wave 3 to wave 4. There seems to be no clear reason for this. However, one reason might be that since the weight $\beta_3$ is increasing significantly, the absolute value of the utility increases significantly too. To compensate for this the weight $\beta_1$ might become smaller, such that the utility as a whole stays approximately the same.

The weight given to the expected standard deviation of travel time in the utility function ($\beta_2$) decreases strongly over waves (in wave 2, 3 and 4 the decreases of $\beta_2$ are 54%, 54% and 77% compared to wave 1). The role of this parameter is to model the weight given to uncertainty about the travel time of the route as a trade-off criterion. The decrease in this parameter might best be interpreted in the light of the finding that the weight given to the expected queue length ($\beta_3$) increases strongly over waves. In wave 2, 3 and 4 the increase
of \( \beta \) is respectively 15\%, 72\% and 246\% compared to wave 1. The importance of expected queue length evidently increases because drivers receive credible information on this. At the same time this information decreases the level of uncertainty drivers experience when making their choices.

To test the significance of each parameter set for each dataset likelihood-ratio tests (Ortuzar & Willumsen, 1990) were performed on data from Table 7.4 which presents the likelihoods for all 16 combinations of datasets and parameter sets. A parameter set denotes the set of parameters that were estimated for a wave. These tests show that, in all cases except one, the estimated parameter set for wave 4 has significantly better fit than all other parameter sets \( (\chi^2(6) > 16.8, p<0.01) \) Only for wave 3 do parameter sets 2 and 3 not differ significantly \( (\chi^2(6) = 1.6, \text{n.s.}) \).

**Table 7.4 Log-likelihoods for all waves by all parameter sets**

<table>
<thead>
<tr>
<th>parameter set 1</th>
<th>wave 1</th>
<th>wave 2</th>
<th>wave 3</th>
<th>wave 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>parameter set 2</td>
<td>-359.4</td>
<td>-457.7</td>
<td>-291.4</td>
<td>-281.0</td>
</tr>
<tr>
<td>parameter set 3</td>
<td>-377.1</td>
<td>-377.4</td>
<td>-240.5</td>
<td>-242.8</td>
</tr>
<tr>
<td>parameter set 4</td>
<td>-389.0</td>
<td>-396.2</td>
<td>-237.9</td>
<td>-233.6</td>
</tr>
<tr>
<td></td>
<td>-423.7</td>
<td>-444.7</td>
<td>-254.4</td>
<td>-213.5</td>
</tr>
</tbody>
</table>

**Simulation**

For each wave parameter estimates were used to perform Monte-Carlo simulations. With these simulations route choice probabilities were generated from (7.6). Experienced travel time is unknown when an individual chooses a different route in the simulation than was observed in reality. To overcome this problem we assume that in these cases experienced travel time equals expected travel time corrected for queue length information according to (7.15) (the experienced queue length is known through the \( RIA_w \) set). This means that when in the simulation a driver chose another route than reported in reality, he experienced what he expected.

From the outcome of these simulations a number of additional statistics were derived. Table 7.5 presents the number of cases in which observed and simulated route choices were the same or differed. For wave 1 the simulation yields the observed choice in 93.5\% of the 3,042 choices. For wave 2, 3 and 4 these percentages are 92\%, 91\% and 89.3\%. Also from these statistics it may be concluded that the model fits well, though the fit decreases significantly over waves.
Table 7.5 Observed versus simulated route choices for all waves

<table>
<thead>
<tr>
<th></th>
<th>wave 1 sim 1</th>
<th>wave 1 sim 2</th>
<th>wave 2 sim 1</th>
<th>wave 2 sim 2</th>
<th>wave 3 sim 1</th>
<th>wave 3 sim 2</th>
<th>wave 4 sim 1</th>
<th>wave 4 sim 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>obs.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1754</td>
<td>108</td>
<td>1292</td>
<td>90</td>
<td>878</td>
<td>81</td>
<td>621</td>
<td>55</td>
</tr>
<tr>
<td>obs.</td>
<td>88</td>
<td>1092</td>
<td>100</td>
<td>884</td>
<td>64</td>
<td>584</td>
<td>69</td>
<td>413</td>
</tr>
<tr>
<td>correct</td>
<td>93.5%</td>
<td>92.0%</td>
<td>91.0%</td>
<td>89.3%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Inspection of errors in the aggregate route 1 and route 2 choices shows that route 1 choices are predicted better than route 2 choices (Table 7.6). On an aggregate level the model performs best for wave 2, second best for wave 1 and worst for wave 4. For all waves the errors are very small, so also on an aggregate level the model performs well.

Table 7.6 Simulation deviations of observed aggregate route choice proportions for all waves

<table>
<thead>
<tr>
<th></th>
<th>wave 1</th>
<th>wave 2</th>
<th>wave 3</th>
<th>wave 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>route 1</td>
<td>-1.1%</td>
<td>0.7%</td>
<td>-1.7%</td>
<td>2.1%</td>
</tr>
<tr>
<td>route 2</td>
<td>1.7%</td>
<td>-1.0%</td>
<td>2.6%</td>
<td>-2.9%</td>
</tr>
</tbody>
</table>

The observed and simulated proportions of route 1 choices per day for all waves are presented in Figures 7.3 through 7.6. Again, these figures indicate that the model performs well for all waves.
Figure 7.2  Simulated vs. observed route choice (wave 1)

Figure 7.3  Simulated vs. observed route choice (wave 2)
\( \chi^2 \) goodness-of-fit tests between observed and simulated data for all waves show that daily aggregate simulated and observed route choices do not differ significantly, again indicating a good model fit (Table 7.7). So the fit of the
model on an aggregate level, i.e. route proportions is determined by a $\chi^2$-test. The fit on a non-aggregate level, i.e. the actual individual choices, is determined by a likelihood procedure.

**Table 7.7 $\chi^2$ goodness of fit for simulations of all waves**

<table>
<thead>
<tr>
<th>wave</th>
<th>$\chi^2$</th>
<th>degrees of freedom</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>wave 1</td>
<td>2.36</td>
<td>15</td>
<td>.001</td>
</tr>
<tr>
<td>wave 2</td>
<td>2.64</td>
<td>15</td>
<td>.001</td>
</tr>
<tr>
<td>wave 3</td>
<td>2.47</td>
<td>15</td>
<td>.001</td>
</tr>
<tr>
<td>wave 4</td>
<td>3.72</td>
<td>15</td>
<td>.001</td>
</tr>
</tbody>
</table>

Model parameters were estimated for a situation without information (wave 1) and situations with information (wave 2 to 4). Using simulated messages as discussed in 7.2, for wave 1 a model was estimated as though information was provided. Further, for waves 2 to 4 the model without information was estimated. These parameter sets were then used to carry out Monte Carlo simulations. Goodness of fit measures of simulations with all parameter sets were calculated for all waves. For wave 1 the fit of the model with information is worse than the fit of the model without information ($\chi^2(15) = 3.26$ respectively 2.36, see Table 7.8). From this it can be concluded that in the first wave, when the RIA-sign was not yet operating, drivers were not fully aware of the queue lengths before the tunnel.

To test whether the information model is necessary to simulate data from wave 2 to 4 the model without information was also estimated for these waves. The results show that in wave 2 and 4 the model with information performs better since $\chi^2$'s are smaller. Only in wave 3 does the model without information perform slightly better ($\chi^2(15) = 2.47$ versus 2.60). We have no indication why this is so.

**Table 7.8 Goodness of fit ($\chi^2$) of simulation models with and without information**

<table>
<thead>
<tr>
<th>wave</th>
<th>no information</th>
<th>with information</th>
</tr>
</thead>
<tbody>
<tr>
<td>wave 1</td>
<td>2.36</td>
<td>3.26</td>
</tr>
<tr>
<td>wave 2</td>
<td>2.65</td>
<td>2.40</td>
</tr>
<tr>
<td>wave 3</td>
<td>2.47</td>
<td>2.60</td>
</tr>
<tr>
<td>wave 4</td>
<td>6.96</td>
<td>3.72</td>
</tr>
</tbody>
</table>
Effect of the variable message sign

One important question has not been answered yet. Does the information on the RIA-sign lead to less experienced congestion? It might be argued that this type of information is useless, because in a situation like this drivers already know what the queue lengths before the two tunnels are. It is conceivable that experienced drivers can predict these queue lengths from the flows they observe, or from other information sources. The model provides the opportunity to test such an hypothesis.

It was already observed that when drivers choose route \( r \) on a certain day, no travel time is known for the other route. Thus, the study does not allow us to determine the benefits of information in terms of travel time. However, the difference in experienced queue lengths in the situation with and without information can be determined. For waves 2 to 4 simulations were performed using parameter estimates of the first wave and using (7.11) instead of (7.16). The resulting choice behaviour mimics a situation in which no information is provided to drivers. This choice behaviour was compared to the actually observed and simulated choice behaviour with information. The results show that information has a considerable effect on experienced queue lengths (Table 7.9). In wave 2, just after the RIA-sign became operational, the simulations show that if no information had been provided drivers would have experienced 2.1\% more queues. In wave 3 this is 9.7\% and in wave 4 11.2\%. So the effect of the information on experienced queue length is evident.

Further it follows from Table 7.9 that the model is also performing very well when comparing the observed experienced queue lengths and the simulated experienced queue lengths.

Table 7.9 Experienced queue lengths (in kilometers) from simulations with and without information

<table>
<thead>
<tr>
<th></th>
<th>observed</th>
<th>simulation with information</th>
<th>simulation without information</th>
<th>effect of information</th>
</tr>
</thead>
<tbody>
<tr>
<td>wave 2</td>
<td>1535</td>
<td>1575</td>
<td>1608</td>
<td>2.10 %</td>
</tr>
<tr>
<td>wave 3</td>
<td>957</td>
<td>961</td>
<td>1054</td>
<td>9.68 %</td>
</tr>
<tr>
<td>wave 4</td>
<td>677</td>
<td>685</td>
<td>762</td>
<td>11.24 %</td>
</tr>
</tbody>
</table>

The above argument can also be reversed. What would drivers have experienced in the first wave, if at that time information had been provided? To answer this question we suppose that the behaviour of drivers in the first wave can be described by the parameters of the second to fourth wave, because these parameter values describe behaviour when information is provided. If the RIA
sign had been operating during wave one the simulated messages would have been displayed to the drivers. If the RIA-messages provide information to the drivers, it may be expected that choice behaviour in which simulated information is put to use, leads to less experienced congestion than choice behaviour which does not use this information. Also it may be expected that the least congestion would be experienced with the parameter set from wave 4, since the results in Table 7.8. already indicate that the effect of information is largest for wave 4. The results (Table 7.10) show that during the first wave a total of 2,081 kilometers queue was observed. The simulation with the estimated parameter set of wave 1 and the model without information also yields exactly 2,081 kilometer queues. The simulations with parameter sets from wave 2 to 4 and the model with information yields total queues of 1,980, 1,934 and 1,897 kilometer. This means that if the RIA sign had been operating during the first wave, and drivers had adjusted their behaviour as they did for instance in wave 4, they would have experienced 7.8% less congestion. These results again show clearly that the provision of information has substantial benefits for the car drivers in terms of experienced queue length.

**Table 7.10** Experienced queue lengths for wave 1, using different parameter sets

<table>
<thead>
<tr>
<th></th>
<th>information assumed</th>
<th>experienced queue length (km)</th>
<th>effect of information</th>
</tr>
</thead>
<tbody>
<tr>
<td>observed</td>
<td>-</td>
<td>2,081</td>
<td>-</td>
</tr>
<tr>
<td>simulation</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>parameters wave 1</td>
<td>no</td>
<td>2,081</td>
<td>-</td>
</tr>
<tr>
<td>parameters wave 2</td>
<td>yes</td>
<td>1,980</td>
<td>4.9 %</td>
</tr>
<tr>
<td>parameters wave 3</td>
<td>yes</td>
<td>1,934</td>
<td>7.1 %</td>
</tr>
<tr>
<td>parameters wave 4</td>
<td>yes</td>
<td>1,897</td>
<td>7.8 %</td>
</tr>
</tbody>
</table>

7.8 Discussion

This study showed that the route choice model which incorporates the processing of information from a variable message sign is a usable tool to simulate real life choice behaviours. Three kinds of results were obtained in this study: model parameter estimates, simulation results and estimates of the effect of the VMS on experienced queue lengths. First of all, the model fitted the data for all waves. Model parameter estimates showed several interesting results. Results for the first wave showed that choice behaviour was almost completely dominated by
habitual choice. It seems that drivers who are very familiar with a choice situation are not utility maximizers. Also, the most recent experience with a route choice was of little importance in this situation. Drivers seem to have made up their minds: dynamic choice behaviour has become static. These results indicate that in familiar choice situations drivers might not be aware of changing circumstances, and that their suboptimal choice behaviour is to a large extent a consequence of habit and to a lesser extent a consequence of faulty expectations. Traditional transport models that adhere to Wardrop's (1952) principles in which drivers are assumed to choose the shortest route, are not valid for the equilibrium situations for which they were originally developed.

After information was provided to the drivers their habit strength decreased, though it still dominated the choice process. Immediately after the RIA-sign was turned on habit dropped by 9%. Also in the following periods habit continued to decrease, though only a few percent. When habit decreased the most recent experience in the learning process became more important. This effect became more pronounced over waves. During wave 4 new expectations are two third of the prior expectations plus one third of the most recent experience. What can be derived from these results is that after information was provided, drivers became utility maximizers to a greater degree than they were before. However, the role of habit was never surpassed by this tendency.

Though results indicated that utility maximization was not the most prominent decision rule, some interesting (and some puzzling) results were obtained from the estimation of the weights for the utility components distinguished. The weight given to expected travel time was stable over the first three waves. In the last wave it dropped by about 10%. We have hypothesized that this was due to the increased weight of queue length in the utility function. The role of expected standard deviation can be translated into uncertainty about expected travel time. The importance of expected standard deviation in travel time decreased significantly over waves. This indicates that the provision of information diminished the uncertainty that was expected as a consequence of prior experiences. This result was expected. In a number of attempts to determine the influence of information on network performance (Koutsopoulos & Lotan, 1989; Hamerslag & Van Berkum, 1992; Cascetta et al., 1992), such a decrease was assumed as a way to model information provision. Although the present results confirm this assumption, they also show that there is definitely more to information provision than merely uncertainty reduction. The importance of the expected queue length and when applicable the reported queue length, in the utility function increased strongly after the VMS became operational.

For all four waves the model fits well. For the first wave the model should not include external information, while for the last three waves the model with information included should be used. This observation becomes most clear when comparing the first and last wave.
This study showed the following concerning the effects of the VMS. Within the setting of this study it could not be determined whether the provision of information actually helped drivers to make a better choice with regard to (total) experienced travel time. However, the difference in experienced queue lengths in the situation with and without information could be determined. A simulation of the choice behaviour for the last two waves with the set of parameters as found for wave one mimics choice behaviour in a situation without information provision. Results showed that information had a considerable effect on the queue lengths that the drivers experienced. In wave 2 drivers would have experienced 2.1% more queues if no information had been provided. In wave 3 and 4 the effect of information was larger, 9.7% and 11.2%. This result shows that the provision of information about queue lengths, even in an environment where drivers are familiar with the situation and no accidents have occurred, has a substantial effect on the experienced queue lengths. Also, it was shown that if drivers had already received information during wave one, they would have experienced up to 7.8% less congestion than they actually did.
Tests and Validation: Prescriptive Information

8.1 Introduction

This chapter presents a second study to test and validate the model on route choice. In this study the model parameters are estimated from two datasets, one concerning a route choice experiment with information from a variable direction sign, and one from a similar experiment without the variable direction sign. Next, by using the estimated parameters, choices generated by the model are compared with those made by the subjects in the two experiments.

For this study data from two route choice experiments were used. These experiments were carried out by Janssen, Van der Horst & Hoekstra (1991) at the TNO Institute for Perception in the Netherlands and by the authors at Bureau Goudappel Coffeng (Van der Mede & Van Berkum, 1992). Janssen et al. (1991) used a driving simulator for their experiments in which a variable direction sign provided drivers with route choice information. In our own experiment data on route choice in a situation without information were collected. This study was originally carried out and reported in the context of the EUROTOPP project (see also EUROTOPP, 1992). In that study it turned out that formal model parameter estimation could not be performed (Van der Mede and Van Berkum, 1992). At the time the study was carried out for the EUROTOPP project no 'standard' procedure to estimate utility maximization parameters, the learning parameter, and habit parameters simultaneously was available. Therefore, the results of that first test could not be interpreted as a validation of the model. However, the results do provide some insight into the sensitivity of the model for different sets of parameters. Some of these results are in Appendix D. In the previous chapter a procedure to simultaneously estimate all relevant model parameters was developed and presented. This estimation procedure will be used again for our present purpose.
Similar to what was done in Chapter 7 it will be necessary to adapt the generic formulation of the model from Chapter 6 to one that is tailored to model the present data.

The chapter has the following structure. In the section on method both experiments from which data were obtained are described. Next, the model which was used to simulate these data is presented in detail. Section 8.3 presents the results of parameter estimation and simulation runs. The final section (8.4) discusses the results.

8.2 Method

Data collection

Experiment by TNO
The TNO experiment (Janssen et al., 1991) consisted of a driver simulator task in which subjects were instructed to choose sequentially between two routes when entering the ringway around Amsterdam (Figure 8.1). Subjects were informed that they arrived at Diemen at 8:30 A.M. and were supposed to arrive at Zaanstad, their presumed work location, at the latest at 9:00 A.M. Subjects who arrived after 9:00 A.M. were fined either one or two guilders for each minute delay\textsuperscript{1}. This fine was subtracted from the fee for participating in the experiments, which was 75 guilders initially.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{two_routes.png}
\caption{The two chosen routes}
\end{figure}

\textsuperscript{1} Subjects participated in different combinations of lay-out of the variable direction sign and pay-off structure.
In the experiment 48 subjects participated, all male. Each subject made 60 sequential choices. Trip performance for each route at each choice was fixed in both time and cost for all subjects as is shown in Figure 8.2.

![Figure 8.2 Trip performance of both routes](image)

The regularly signposted route to Zaanstad was route one. In all instances when the variable direction sign was operational drivers were advised to use route two. The dotted vertical lines in Figure 8.2 indicate the fourteen choices for which the variable direction sign was operational. Choice series for all subjects were recorded.

*Experiment by BGC*

The second experiment was carried out at Bureau Goudappel Coffeng (BGC). The overall structure of the experiment was similar to the TNO experiment, with the major difference, that no variable direction sign route information was provided to the subjects. Instead of a driver simulator, a choice-game on a personal computer was developed to collect the data. At the beginning of the experiment subjects were informed that route one was the signposted route to their destination. After each choice, travel time and costs for the previous trip were presented to the subjects. In this game arriving late was not fined. Instead, the subject who performed with the smallest overall delay won a gift voucher for a compact disc. 34 subjects participated, 28 male. Choice series for all subjects were recorded.
Model description

Expected Utility Function
For this study the generic formulation of a random utility function (Chapter 6) must be made specific. Both experiments suggest that next to travel time subjects may be sensitive to travel costs. Three terms in the expected utility function (8.1) are immediately related to this assumption. Expectations about the outcome of travel time and costs are captured by expected means for these attributes. Individual uncertainty about variations in travel time outcomes is captured by experienced variance in travel time outcomes.

To model the experimental data the following expected utility function was used:

\[ V_{irt} = \beta_1 t_{irt} + \beta_2 s_{irt} + \beta_3 k_{irt} \]  \hspace{1cm} (8.1)

with

\[
\begin{align*}
    t_{irt} & \quad \text{expected travel time by individual } i \text{ for route } r \text{ at choice } t \\
    s_{irt} & \quad \text{expected standard deviation of travel time} \\
    k_{irt} & \quad \text{expected travel costs} \\
    \beta_1, \beta_2, \beta_3 & \quad \text{utility parameters}
\end{align*}
\]

We will use the term expectations as identical to expected utility.

Initial Expectations
The initially expected means and variances of travel times and costs for both alternatives influence the choice behavior. The definition of the dynamic choice structure needs specification of initial values of all elements of the expected utility function.

In both experiments the initial values are not influenced by previous experiences as was the case in the field study from Chapter 7, where drivers already had experience with the routes in the study. Two assumptions about the values of the initially expected travel times seem plausible. The first is that since subjects are not provided with specific information about expected travel times on either route, they would expect them to be equal. The second is that because usually route one is advised, this might imply that subjects would tend to expect a smaller travel time on this route than on route two. As to the actual values of these initial expectations it seems likely that subjects would expect to arrive at their destination within the 30 minutes allowed. At the start off the simulations two sets of initial values were used, namely 30 minutes for both routes, or 25 minutes for route one and 28 minutes for route two. The latter equals the average performance over both routes after sixty choices. For both sets of initial values, identical arguments for establishing initial cost expectations were used. More or less in line with the previous, since subjects did not have any information
on variances in travel time, initial expectations can be assumed zero. On the other hand, it also seems likely that people would expect some variance, since the nature of the experiment indicates this. Therefore, also two sets of initially expected standard deviations\(^2\) for travel time were used to start off the simulations. The first with zero initially expected standard deviation, the second with the square root of mean expected travel times. Updates of initially expected zero variances can only start at the third choice, since for updating purposes at least two experiences must be present. After the second choice, expectations will be updated according the procedure described in the next section about updating expectations.

**Updating Expectations**

Each choice results in a trip with a certain travel time and costs. The strategy used to update expectations over choices will influence the resulting choice behaviour. Mean expectations of travel time and costs are updated according to the dynamic formulation of expected travel time as defined in Chapter 6 (see (6.7))

\[
t_{ir}^t = \delta_{ir,t-1} (\psi t_{ir,t-1} + 1 - \psi) + (1 - \delta_{ir,t-1}) t_{ir,t-1}
\]  

(8.2)

with

- \(et_{ir}^t\) experienced travel time at choice \(t\)
- \(\psi\) learning parameter

The dynamic formulation of expected costs is defined in a similar way

\[
k_{ir}^t = \delta_{ir,t-1} (\psi k_{ir,t-1} + 1 - \psi) + (1 - \delta_{ir,t-1}) k_{ir,t-1}
\]  

(8.3)

with

- \(ek_{ir}^t\) experienced costs
- \(\psi\) learning parameter

The dynamic formulation of the expected standard deviation in travel time is exactly as defined in (6.10).

\(\psi\) reflects the importance of the last experience versus an average expectation based on the history of choices. If \(\psi = 0\), the subject's 'memory' reaches only to his most recent experience. Dependent on the outcomes of choices, this can lead to highly dynamic choice behavior. If \(\psi = 1\) the subject hardly learns from experience, because only average performance is evaluated. In that case, in the long run \(t_{ir}^t \approx t_{ir,t-1}\), and will become largely independent of \(et_{ir,t}^t\). This means that subjects will barely react to changes in the outcome of their choices.

---

\(^2\) To stay in line with Chapter 7 standard deviation instead of variance is used
In both experiment a logit model is assumed for route choice, such that

\[ P(U_{irt}) = \frac{e^{V_{in}}}{e^{V_{in}} + e^{V_{in}}} \]  

(8.5)

with \( V_{irt} \) as defined in (8.1)

**Habit**

The development of habit over choices is assumed to depend on two parameters: the importance of the former choice (\( \gamma \)), and the number of choices needed to reach \( H_{\text{max}} (\alpha) \). In contrast to the study presented in Chapter 7 no initial habit can be assumed, because subjects did not have any experience with the choice situation previous to the experiment. Therefore, \( H_{ij} \) is assumed to be zero. This implies that for the present study estimation of parameter \( \alpha \) is necessary, unlike in the previous chapter where \( H_{ij} = H_{\text{max}} \) was assumed.

In updating habit as in Chapter 7 no assessment of the experience with the chosen route is included. This means that \( \omega_{it} = 1 \) for all \( i \) and \( t \). Each individual chooses a route for each \( t \), so \( \delta_{it} + \delta_{it} = 1 \). Using (6.20) with the above observations the probability that a route is chosen habitually becomes

\[ P(IN_{irt}) = \frac{\gamma P(IN_{ir,t-1} + \delta_{ir,t-1})}{\gamma + 1} \]  

(8.6)

**Compliance with the Variable Direction Sign**

We assumed that user responses to the variable direction sign are contingent on trip performance. Drivers may react to the advice in different ways. Their experience will vary according to their decisions and the credibility and exclusiveness of the information provided. In general it may be assumed that the proportion of drivers who comply with the advice, depends also on their need for information. Since the pay-off strategy in the experiment demands high performance of all subjects, a high need for information may be assumed.

To simulate the experimental data, some initial compliance rate \( PC_{ij} \) must be assumed the first time the variable direction sign is operational (at choice 11), because at that point subjects do not have any experience with the variable direction sign. We will return to this later.

The variable direction sign provides prescriptive information, hence responses to the sign are modelled as a separate decision rule. Drivers either comply with the advice or ignore it. In case of compliance, both utility maximization and habit are overruled.

User responses to the variable direction sign were modelled as a probability to comply with the given advice as described in Chapter 6. The propensity to comply is assumed contingent on experience. Generally, good experiences
will lead to increased compliance, bad experiences will lead to a decrease. The opposite holds for subjects who do not comply. The compliance algorithm concurs with these behavioral assumptions. However, formal validation of the algorithm was not carried out. The value of parameter $PC_{ij}$, followed from inspection of choice behavior of subjects at the first choice when the variable direction sign was operational. At that point a compliance rate of about 96% was evident.

Thus the compliance update scheme as defined in Section 6.1.7 was applied. From inspection of the compliance rates as found in the experiment a good value for $\xi$ turned out to be 5, and $B_{\text{max}}$ was set to 3. Further $PC_{ij}$ was set to 0.96 for all individuals.

**Estimation and Simulation**

To estimate $\beta$’s for all components of the expected utility function (8.1), the learning parameter $\psi$ and the habit parameter $H_{\text{max}}$, $\alpha$ and $\gamma$, the estimation procedure presented in Chapter 7 and Appendix A was used. Trip performance according to Figure 8.2 were used. Two initial expectations value sets were studied. Each time the complete specified model for each of the datasets was estimated.

For both experiments the log-likelihood function becomes:

$$\mathcal{L} = \sum_i \sum_{t=1}^{60} \log \left( \prod_{r=1}^{2} (1 - \delta_{irr}) + \sum_{r=1}^{2} \delta_{irr} P_{irr} \right)$$  \hspace{1cm} (8.6)

Since in the BGC experiment no information was provided it holds that

$$P_{irr} = H_{ii} \cdot PIN_{irr} \cdot (1 - H_{ii}) \cdot PUM_{irr}$$  \hspace{1cm} (8.7)

For the TNO experiment it holds that

$$P_{i1t} = [vds_{it}(1 - PC_{it}) + (1 - vds_{it})] [H_{it} \cdot PIN_{i1t} \cdot (1 - H_{it}) \cdot PUM_{i1t}]$$  \hspace{1cm} (8.8)

$$P_{i2t} = vds_{it} \cdot PC_{it} \cdot [vds_{it}(1 - PC_{it}) + (1 - vds_{it})] [H_{it} \cdot PIN_{i2t} \cdot (1 - H_{it}) \cdot PUM_{i2t}]$$  \hspace{1cm} (8.9)

where $vds_{it}$ is a variable that is 1 when the direction sign is on (and advises route 2), and 0 otherwise.

**8.3 Results**

An overview of the estimation results for TNO and BGC data is presented in Table 8.1. From the estimated loglikelihoods $\mathcal{L}(\hat{x})$ and the $R^2$ of the models it is clear that the model for the TNO data shows a better fit than the model for BGC data. For the TNO data the model predicts 95% of the route one,
and 86% of the route two choices correctly. The model for the BGC data predicts 88% of the route one, but only 35% of the route two choices correctly.

For the TNO data the best fitting initial values for expected travel times are 25 and 28 minutes for route one and two respectively. For the BGC data initially expected travel times of 30 minutes for both routes performed best. This indicates that the two experiments are not completely comparable. We will return to this later on.

Table 8.1 Parameter estimates for TNO and BGC datasets from simultaneous maximum likelihood estimation

<table>
<thead>
<tr>
<th>initially expected travel time</th>
<th>TNO</th>
<th>BGC</th>
</tr>
</thead>
<tbody>
<tr>
<td>parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( H_{\text{max}} )</td>
<td>0.98</td>
<td>0.25</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>1.1</td>
<td>5.8</td>
</tr>
<tr>
<td>( \psi )</td>
<td>0.12</td>
<td>0.44</td>
</tr>
<tr>
<td>( \beta_1 ) (travel time)</td>
<td>-30</td>
<td>-27</td>
</tr>
<tr>
<td>( \beta_2 ) (std. deviation travel time)</td>
<td>-10</td>
<td>-5.5</td>
</tr>
<tr>
<td>( \beta_3 ) (travel costs)</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>-0.1</td>
<td>-0.1</td>
</tr>
</tbody>
</table>

| summary statistics            |      |      |
|\( L(0) \)                     | -1624.8| -980.7|
|\( L(x^*) \)                   | -331.9 | -589.3|
|\( \rho^2 \)                   | 0.80  | 0.40 |

There is a marked difference between the amount of habitual choices in the TNO and BGC experiment. Estimates for \( H_{\text{max}} \) were respectively 0.98 and 0.25. Clearly, BGC subjects made substantially fewer habitual choices than did TNO subjects. \( H_{\text{max}} \) is dependent on \( \alpha \), but estimated values for \( \alpha \) for TNO and BGC data are identical. So the speed with which habit is built up is the same in both experiments.

The weight of the most recent experience in the updating of expectations \((1-\psi)\) is largest for the TNO data. So, although TNO subjects base their choice more frequently on habit than BGC subjects, they also take recent experiences more strongly into account when they update their expectations. Weights for the most recent experience for both datasets are greater than the ones found for the four waves of the panel.
The stability of the distribution of habit strength over the two routes seems to be somewhat higher for the BGC than TNO subjects. However, compared to the values found in Chapter 7 for the four waves of the panel, both values for $\gamma$ are small, indicating relatively unstable habits for both routes.

Parameter estimates were consequently used in a Monte-Carlo simulation to simulate the TNO and BGC data.

To compare the aggregate outcome of the simulation runs with the original TNO and BGC datasets a number of benchmarks were calculated. These are:
- mean number of route switches per individual;
- percentage of route one choices;
- percentage of choices which were based on habit. Of course this benchmark cannot be compared to the original data, since the presence of habitual choice can only be inferred from the data;
- mean costs and mean excess travel time per individual. I.e. the time that an individual spent more than in case the fastest route would have been chosen each time.

Table 8.2 present aggregate results of the simulations (SIM) compared to the experimentally obtained TNO and BGC datasets (EXP). The benchmarks for simulations demonstrate that BGC subjects based a total of 13.7% of their choices on habit, while TNO subject made 48.9% habitual choices. Both percentages are smaller than the ones found for the four waves of the panel in Chapter 7.

<table>
<thead>
<tr>
<th>switches</th>
<th>% route 1</th>
<th>% habit</th>
<th>costs</th>
<th>excess travel time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TNO</td>
<td>BGC</td>
<td>TNO</td>
<td>BGC</td>
</tr>
<tr>
<td>EXP</td>
<td>25.9</td>
<td>10.1</td>
<td>77.8</td>
<td>85.9</td>
</tr>
<tr>
<td>SIM</td>
<td>24.9</td>
<td>7.1</td>
<td>77.2</td>
<td>83.5</td>
</tr>
</tbody>
</table>

On the aggregate level only minor differences between observed and simulated data exist; again this indicates that the model fits the data well. Results indicate that habit is a necessary model component to simulate both datasets.

Aggregate percentages of route one choices from simulation are presented in Figures 8.3 and 8.4. The figure for the BGC simulation indicates that the model is somewhat more sensitive to travel time and costs variations than real subjects are. For instance, at choice 29 subjects experience a 10 minute delay
when they make a route one choice (see Figure 8.2). If they choose route one, the effect of this 'mistake' is quite clear at choice 30 when only 50% of the simulated subjects make a route one choice again. Still, on the whole the simulation is remarkably similar to the observed behaviour.

![Percentage route 1 choice: BGC data and simulation](image)

**Figure 8.3** Percentage route 1 choice: BGC data and simulation

The performance of the module which simulates responses to the variable direction sign is best illustrated by Figure 8.4. The response pattern starts at choice eleven, when the variable direction sign is operational the first time. The proportion of subjects that choose route two is 96% at that point. For that choice compliance with this advice leads to a two minute delay, and the route two proportion drops to about 80% at choice fourteen, the next time the variable direction sign is operational. For this choice, compliance with the advice leads to a 5 minute delay. After this choice the proportion of subjects that chooses route 2 drops to about 45% at choice seventeen. At that point compliance with the advice results in timely arrival, and ignoring it leads to a three minute delay. After choice seventeen the route two proportion steadily increases to over 90% at choice 40, when a wrong advice is given once more. This leads to a one minute delay. This delay hardly results in a decreased proportion of route two choices at choice 43. This can be understood, because by then, subjects have experienced a series of six good advices.
Figure 8.4 Percentage route 1 choice: TNO data and simulation

There is a noticeable difference in route choice behaviour during the first ten choices for TNO and BGC subjects. Over 90% of the TNO subjects chose route one the first time, while only 50% of BGC subject did so. The TNO experiment suggests more clearly than the BGC one that route one is normally the best route. Although this was mentioned in the instruction of the BGC subjects, TNO subjects were confronted with this fact for each choice (when the variable direction sign was off). Therefore, the initial values for expected travel time that performed best in the TNO experiment are 25 minutes for route one and 28 minutes for route two. For the BGC experiment initial values of 30 minutes for both routes resulted in the best performance of the model.

8.4 Discussion

In this study we tested and validated the model which simulates individual route choice behaviors in a situation with and without information from a variable direction sign. The results indicate that the presented model can simulate the datasets which the experiments yielded very well.

In accordance with the results from Chapter 7 the results strongly support the assumption that habit is a necessary model component, both for situations with and without prescriptive information. The fit of simulation results was best for the TNO data. Differences between both experiments in the laboratory settings, a driving simulator for the TNO experiment, and a computergame for the BGC experiment, can be related to this finding. It may be that BGC
subjects were forced to take higher risks (to win from their opponents), than TNO subjects, who may have been more prone to reduce risk (to lose less money). Another factor may be that the task in the BGC experiment seems more difficult since more uncertainty is involved. From statements made by subjects during the experiment we got the impression that they were searching for a strategy which could solve their problem. Some even stated that they had found the 'solution', though of course there was none. The task in the TNO experiment seems easier, because route choice advice was given to the subjects. Although we dismissed these kinds of effects as being too specific in Chapter 4, it seems that the influence of the task setting must be considered, at least when conducting laboratory experiments.

Another possible explanation for the difference between the estimated amount of habit in both experiments follows from the present model specification. In the BGC experiment two choice rules can apply, habit or utility maximization. In the TNO experiment compliance is a third possible choice rule. If the relevant choice rules were to be applied with equal probabilities in the TNO and BGC experiment, the probability that a choice is based on habit would be greatest in the BGC experiment. The data show that this is not the case. A closer look at the aggregate choice pattern in Figure 8.4 indicates that it seems possible to simulate this pattern with only two choice rules: compliance and habit. The choice strategy would be: if the variable message sign is on use the compliance rule (so either comply with the advice or ignore it), else, perform habitual choice. The large amount of habit in the TNO experiment seems to indicate such a choice strategy.

This argument, however, can be extended. In fact, it seems possible to simulate the TNO-data using a single choice rule, i.e. by generalizing the compliance rule. In the present model specification we assumed that the variable direction sign is off when route one is advised. It can be argued however, that the variable direction sign is always on, irrespective of the advice it provides. If the model were to be specified accordingly, the credibility of the advice, and compliance with it, would have to be specified contingent on the direction indicated by the sign. From the trip performance (Figure 8.2) it is evident that route one advices were always correct. So maximum credibility and maximum compliance with route one advices would result. So, by generalizing the compliance rule it seems possible to model the same behaviour as was now modelled by the habit rule. The above does not mean that the habit rule, or utility maximization for that matter, are superfluous choice rules. However, it does mean, that due to the trip performance in the present experiments, we cannot draw final conclusions on the relative importance of the three choice rules, in a situation with prescriptive information. In future experiments trip performance must be varied systematically. From these experiments it can become clear whether it is indeed better to specify the more general version of the compliance rule (as in the generic model formulation in Chapter 6) to simulate variable direction
signs, or to distinguish situations in which the sign is on and off as was done in the present study.

The results of the TNO experiment indicate that the consequences of flaws in the reliability of information systems, at least the type used here, are not as dramatic for their credibility as often expected. At least in the laboratory situation, drivers recover fast after bad experiences with the variable direction sign, and never lose faith completely. The responses to the variable direction sign can be modelled well by a probability of compliance that incorporates a buffer.

The differences between the performance of the subjects in the two experiments indicates the importance of information. Of course, laboratory experiments in which trip performance is fixed are not designed to estimate the benefits of information in a real life situation.
Conclusions and Implications

9.1 Introduction

In this final chapter conclusions from our study will be drawn and the implications of the findings discussed. The chapter will make clear to what extent the research has been successful in reaching the objectives of the study, and indicates what is left to be done. New questions emerging from this research are put forward.

The chapter has the following structure. In Section 9.2 the research goal will be stated once more. Section 9.3 discusses the major research findings. In that section conclusions about the development of the methodology and about the validation of the methodology are presented. In addition a number of important implications of the findings are discussed. In Section 9.4 we elaborate on a number of questions that remain concerning the methodology. Finally, in Section 9.5 recommendations for future research are presented.

9.2 Research Goals

The main research goal of this thesis is to develop and validate a methodology to predict or estimate the influence of different, new information systems for car drivers. The motivation for this research lies in the observation that excess travel can result from the fact that car drivers lack information. It seems that many drivers aim to minimize the time or distance travelled, but they sometimes lack the information to succeed in this. Since a number of newly developed information technologies provide the opportunity to inform drivers more adequately, the question emerges to what extent these information technologies can contribute to better travel choices, and reduce excess travel.

The major reason to develop a new model is that traditional transport models are not suited to deal with information adequately. They either assume travellers to be perfectly informed, are static, or treat information as an abstract quality.
The newly developed model is specifically designed to deal with information. It links existing traffic modelling notions to a number of behavioural concepts. We will now turn to the question to what extent the research goals of this dissertation were reached.

9.3 Conclusions

Information Systems
In Chapter 2 it was shown that in transport a broad variety of new information systems exist and are under development. The model which was developed deals with information systems that are relevant to route and departure time choice.

Information was distinguished by a number of aspects. The most important distinction was between descriptive and prescriptive information. In addition to this distinction, information can vary in its timing and location (pre-trip and en-route). Concerning these distinctions, it can be concluded that the developed model can deal with both prescriptive and descriptive pre-trip and en-route information.

Returning to the overview of information systems provided in Chapter 2, it seems that the model is particularly useful to study the effects of the following types of information systems: electronic route planning and other pre-trip information systems, all types of guidance systems, and variable message signs. The model cannot address the effects of on-board directional aids and location displays. To explain why this is so, the assumption that any message provided by the information systems under consideration can be decomposed into prescriptive messages and descriptive messages needs some further specification: the assumption only holds for messages with a clear structure. Clear structure was evident in the information used in the empirical studies we carried out. For on-board directional aids and location displays this is not true. Although both types of systems also provide map information (which has clear structure), additional information can be the current vehicle location and a compass. This type of information has no clear structure. An additional problem is that, for safety reasons, most of these systems can only be consulted when the car is stopped. So even if it were possible to translate locational and directional information into some message with clear structure, it would be impossible to know when a driver would stop his car to consult the device, or what he would see on it.
Existing Modelling Approaches

In Chapter 3 existing modelling approaches were reviewed. They were classified according to three main characteristics: (a) static versus dynamic; (b) deterministic versus stochastic and (c) equilibrium versus non-equilibrium.

It was observed that the introduction of the dimension time in models does not equal dynamics. Only when time is used as a framework, and thus has to do with changes over time, and the dependency of the traffic situation in consecutive time periods, can the term dynamics be used.

Concerning dynamics it was stated that two main types of dynamics exist, within-day dynamics and day-to-day dynamics. Within-day dynamics treat time dependent states within the solution method, i.e. traffic flows in period \( t + 1 \) depend on flows in period \( t \). The second type of dynamics more explicitly models the time dependency in individual choice behaviour.

It was concluded that static and deterministic approaches are not suited to determine the impact of traffic information. The approach we adopted is a day-to-day dynamic, and stochastic approach. Further, it was found that, to determine the effect of information, information (systems) should be modelled explicitly. Further, to deal with information, it is necessary to include individual expectations in the model. From this it followed that our approach should be oriented towards individual car drivers. It became clear that currently no model exists that carries all the necessary elements. However, some necessary pieces of the model are present in existing models. These pieces are: (a) the concept of learning (Horowitz, 1984), (b) the joint modelling of route and departure time choice (Ben-Akiva et al., 1984), however, modelling must be done simultaneously instead of sequentially, (c) the individual approach and the concept of bounded rationality (Mahmassani and Herman, 1984). Further, Mahmassani’s modelling framework in which a learning module and information processing module are integrated, was found to be a good start for our modelling effort.

Concerning the way in which existing approaches deal with information it was concluded that none of these do this in an appealing manner: either information is regarded as an abstract, uncertainty reducing quality, or the information system is specific but highly unrealistic. In none of these approaches are attempts made to model individual choice behaviour other than by perceived utility maximization, or by a switching rule based on the concept of bounded rationality. Thus, we could not adopt the way in which information is modelled from existing approaches.

Ben-Akiva et al. (1991) proposed a framework that can be described by a number of difference equations, just as we did in our model. However, Ben-Akiva aims to solve these equations, because he is looking for a stationary state. This can only be done when the strict and unrealistic assumption is made that information itself is also a stationary process. In our model we do not aim to find a stationary solution, because our interest lies in the description of the process. In our approach the solution is the set of parameters that describe
the model as a whole. With these parameters the dynamic *process* is defined, irrespective of the information contents.

In summary, we conclude that some of the existing models include (partly) useful concepts, though in all approaches, individual behaviour and information are never modelled adequately. In our modelling effort we have solved these shortcomings.

After we have discussed the validation of our model, we will return to the question how wrong the existing approaches are to model situations in which no exogenous information is provided. How our model performs in environments with information cannot be compared with existing approaches, because these cannot deal with information.

**Individual Choice Behaviour**

To improve the behavioural basis for the model, the objective of Chapter 4 was to take into account relevant findings from behavioural research. Only few usable findings resulted from this review, but Rapoport's (1975) definition of dynamic decision making proved to be valuable to develop further our ideas about the necessary behavioural model components. This definition states that dynamic decision making involves decisions that are made sequentially in time. The task specifications may change over time independently or as a result of previous decisions. This implies that both choice and learning from experience must be part of the model. It became clear that dynamic decision making is a neglected research area.

It was found that many different choice models exist. Generally, these can be divided into normative and descriptive models. Although it was found that descriptive models are superior, no such model which could serve our purpose has been developed yet. It was concluded that the widely used, expected utility maximization model is the best available option in this context. It is computational easy to handle, and necessary data are not too difficult to collect.

Yet, this could not be the only decision rule. In a situation in which choices are made repeatedly over time, the necessary high level of cognitive processing implied by utility maximization, will probably not always exist. Therefore, an additional choice rule, that requires less cognitive processing, had to be included. We call this rule habit.

In situations in which exogenous information is provided, both choice rules can be operational. However, in situations in which prescriptive information is provided, another additional choice rule was included. This rule describes whether or not the advice is followed. This rule is called compliance.

**Assumptions and Foundations**

From the conclusions from Chapters 2, 3 and 4, the assumptions and foundations that underlie the model were formulated.
the model should be day-to-day dynamic, stochastic. The 'solution' is not a stationary state, but a description of all parameters of the processes in the model;
- the model should be suited to deal with prescriptive and descriptive information;
- the model should be suited to deal with pre-trip and en-route information;
- individual expectations should be modelled;
- individual knowledge can be divided knowledge on the structure of the network, and expectations about performance;
- the model should contain three decision rules: (i) habit, (ii) perceived utility maximization (also valid to process descriptive information) and (iii) compliance with the advice (to process prescriptive information);
- expectations are made contingent on previous experiences using a learning model;
- habit is contingent on previous choices;
- the credibility of the information is contingent on previous experiences with the information system;
- credibility controls the level of compliance and the extent to which descriptive information is used in the utility maximization rule.

Development of the Methodology
As far as the development of the methodology is concerned, a comprehensive framework to model route and departure time choice under distinct information scenarios, i.e. prescriptive and descriptive information, was developed. In the description of the model emphasis lies on route choice. The reasons for this are: (a) the departure time choice process can be modelled analogous to the route choice process and (b) route choice is the most complex of the two.

We have seen that quite a large number of behavioural assumptions were necessary to specify the methodology. It was shown that the - often implicit - behavioural assumptions from which traditional transport models were developed, lack theoretical profundity and comprehensiveness. Also it was shown that behavioural science does not yet provide a well-defined descriptive theory on dynamic choice behaviour in general, or on route and departure time choice in particular. The work that was presented in this thesis may therefore also be regarded as an attempt to formulate a more comprehensive theoretical framework to model route and departure time choice. Behavioural theory, and particularly theory on decision making, unfortunately does not provide much evidence as to whether or not many of the assumptions made are valid. Therefore, the empirical work presented in this thesis is also a first attempt to validate these assumptions. We will return to this later.

The essentials of the complete model we developed can be described as follows. The model deals with route and departure time choice of car drivers on an individual level. For each individual a set of known routes is generated. Individual
route choice sets are generated in such a way that longer routes are less frequently known than shorter ones. The size of the choice sets is initially assumed to be fixed and can only change as a result of external information.

In situations without external information systems drivers base their choice either on perceived utility maximization or habit. The model is suited to deal with prescriptive and descriptive traffic information provided pre-trip or en-route. The model focuses on day-to-day dynamics in choice behaviour. It can take into account within trip adaptive route choice behaviour when traffic information is provided en-route. Drivers learn from their experience on a day-to-day basis. In this way experience influences expectations on which choice behaviour is based. Drivers' responses to traffic information depend on two things: the credibility and the net value of the information.

Known route sets and expectations about performance differ among drivers. The influence of information on a driver's choice behaviour depends on its net value, i.e. the difference between the information and individual expectations. Therefore, identical traffic information is interpreted differently by various drivers. Consequently, the influence of information on choice behaviour is modelled on an individual, non-aggregate level.

In contrast to traditional transport models, that assume travellers use a single decision rule to choose between alternatives, in the present model, in situations without external information, two decision rules can be operational (though only one at a time). Next to the more or less standard, (perceived) utility maximization rule, habitual choice is incorporated in the model. Habit is defined as repeating previous choice behaviour without making a trade-off between available alternatives. Habitual choice is conceived to be dependent on three parameters: maximum habit strength ($H_{max}$), the speed with which habit strength builds up over choices ($\alpha$), and the stability of habit strength when choices vary ($\gamma$).

In addition to situations without external information the model is suited to deal with situations in which different types of traffic information are provided to drivers. Concerning the types of traffic information the distinction between descriptive and prescriptive information turned out to be a useful one. This simple distinction allows for differentiation in information processing which is necessary from a modelling point of view. Descriptive information is processed in line with the perceived utility maximization rule, while prescriptive information is followed up or not. This means that next to the utility maximization and habitual choice rules, a third decision rule within the model is compliance. Obviously, this rule is only operational when drivers are provided with prescriptive information.

Compliance with information is modelled as a direct result of the credibility of information. In fact, compliance, being a value between 0 (no compliance) and 1 (full compliance) is modelled as identical to the credibility of the information, which is also a value between 0 (information is not believed) and
1 (information is completely believed). So a trade-off is always made between the information and the driver's expectations and habit. Lack of credibility of information results from bad experiences with this information. As a consequence drivers will follow such information to a lesser degree. The degree of compliance with information is modelled as a consequence of 'good' and 'bad' experiences that drivers have with the information (system). Good and bad experiences are determined from the difference between the experiences and expectations.

Credibility of descriptive and prescriptive information is determined in a similar way. The credibility of both types of information is based on a comparison of 'outcomes' and expectations. In both cases the comparison is made after the trip is performed. When a route is chosen that does not contain the path the information is about, only the credibility of prescriptive information can be updated from the trip performance. For descriptive information credibility cannot be updated in that case.

It is too early to give a final judgement on the completeness of the model as a whole. However, the empirical studies indicated that the methodology concerning route choice under different information scenarios is sufficiently developed to serve its purpose. The completeness of the methodology on departure time choice is still uncertain because this part of the model was not validated in the study, due to a lack of data.

One element of the proposed methodology, the dynamic loading technique that assigns cars to the network, has not yet been developed sufficiently. Though such a loading technique is necessary, its absence did not hinder the development of the model, or validation of the route choice processes, because trip performance data were available. In general, for situations in which dynamic performance data are available this allows for estimation and prediction of effects of information on an individual level. However, for a more general application of the model performance data must be generated by a dynamic loading technique, which as a consequence must be linked to the model.

Validation of the Methodology
In two studies the route choice model was validated for prescriptive and descriptive information. The model for route choice under descriptive information was validated with data from a field study. The model for prescriptive information was validated with data from laboratory experiments. A general conclusion from these studies is that the model is suited to simulate individual route choice data obtained from both field studies and laboratory experiments. Because performance data were available to estimate model parameters, the absence of a loading technique caused no problems for the validation studies. In fact, it is impossible to validate the choice model and loading technique simultaneously,
because any difference between the actual situation within the traffic system and the model may result from either errors in the behavioural model or in the loading technique, or in both. The cause of these errors would be impossible to trace.

Results of both validation studies demonstrate that the route choice process has (at least) the dual character which was assumed. Both studies provide clear evidence for the assumption that habit is an important decision rule to model route choices. Habit turns out to be even more important than anticipated, although it never completely eradicates utility maximization as a decision rule. The importance of habit has some strong implications for the validity of traditional traffic models. We will return to these implications later on. Also, the finding that utility maximization still plays some role in the decision process is important: if habit were the only decision rule operational, this would mean that in the current model environment drivers would not be sensitive to descriptive information. It can be argued however, that descriptive information influences habit strength. In our studies habit strength was modelled as being dependent only the maximum amount of habit strength and the number of good experiences. This formulation could be rephrased by defining habit strength to be dependent on the existence of descriptive information too.

Within the general specification of the model habit is assumed to be sensitive to deterioration of performance. So, habitual strength is modelled to diminish when the actual experienced travel time exceeds the expected travel time by more than a threshold value. The results of the empirical studies did not provide evidence that it is necessary to incorporate this aspect of the model, or, more correctly, it seems that in none of the studies this threshold was reached. However, an exception could be the BGC experiment. In this experiment the observed route choices were far from optimal, so a lot of bad experiences were registered. It may be, that if diminishing habit as a result of bad experiences would have been incorporated within the estimated model, that estimated value of $H_{max}$, the maximum habit strength, would have been larger.

We stated that habit and inertia are not interchangeable. Habit means that an individual repeats his prior behaviour. Inertia means that when there is a change in the transport system, individuals will not immediately respond to this change. In the model the latter effect can be produced by both habit and by learning.

The importance of habit has certainly been recognized in the past (Benshoof 1972). This study shows that it indeed must and can be modelled. This demonstrates what everyone interested in route choice modelling long assumed, namely that what has become known as Wardrop's equilibrium principle (Wardrop, 1952) is an erroneous description of reality. This principle states that the travel time of all routes used between a particular origin and destination are equal to or shorter than those of non-utilized routes. Wardrop's principle is based on 'objective' utilities, i.e. real travel times, travel costs etcetera. Sheffi (1985) has reformulated this principle according to perceived utility notions,
and states that 'In the equilibrium situation, no single traveller can increase his subjective utility by unilaterally changing his route'. A fundamental problem with this principle is that it is not possible to falsify it, because the argument why perceived utility models do not fit the data can always be transferred to imperfections in the measurement of subjective utility.

The present study demonstrates that from a modeller's point of view it is much easier to incorporate habit than to try to improve the measurement of subjective utility. Also, our study shows that incorporating habit as a decision rule within the model makes efforts to improve measurements of subjective utility superfluous. Furthermore, from a behavioural point of view the presence of habit in choice behaviour is very plausible, and the present model therefore provides a more accurate description of choice behaviour.

*How valid are the behavioural assumptions we made?*

The work presented in this thesis was not primarily aimed to develop and validate a behavioural theory on route and departure time choice. Still, we have presented a number of behavioural assumptions which constitute a framework for modelling these behaviours. The results do not allow conclusions on the validity of the complete framework, but two conclusions concerning the proposed learning process and choice rules can be formulated.

The first is that learning behaviour is a necessary behavioural component of this framework. The empirical studies demonstrated that the value for the learning parameter $\psi < 1$. This shows that it is not valid to assume fixed expectations in day-to-day route choice behaviour. The second conclusion is that, since the proposed choice rules allowed us to model the data well, these rules are both necessary and sufficient to describe route choice behaviours.

We feel that the results we obtained with our model are promising, and find that further research into the validity of our assumptions is necessary. We will return to this in the last section of this chapter.

*How wrong are traditional models?*

A general question that arises from our research is: how wrong are traditional traffic models? We have already dismissed the principles formulated by Wardrop (1952) and Sheffi (1985). However, more can be said about the errors which are made by traditional models.

To set up a line of argument a strict view on dynamics and equilibrium must be adopted. Let $S_t$ denote the state of the transport system at day $t$, and let $B_t$ denote the route choice behaviour of drivers at day $t$. An equilibrium approach assumes that drivers are (subjective) utility maximizers. In general, a traffic system is said to be in equilibrium if $B_t$ is in accordance with $S_t$, so drivers are behaving according to what is going on in the transport system. This implies that drivers use the state of the system to determine their behaviour, using the rule of utility maximization. Of course, the sum of all individual behaviours
is supposed to be a description of the state of the traffic system. However, in equilibrium approaches it is not clear whether the individual behaviours lead to the traffic state or vice versa. In fact, the whole notion that such an equilibrium would occur is highly questionable.

Contrary to this, our model provides a clear link between individual behaviour and the state of the traffic system. In our model the state of the traffic system at day $t$ is a result of the individual behaviours at day $t$, which in turn are a result of experienced previous states and a result of previous behaviours (Figure 9.1).

![Figure 9.1 Dynamic structure of the model](image)

In most existing *dynamic* day-to-day models choice behaviour is assumed to be dependent on previous states but not on previous behaviours, i.e. habit is not included (Figure 9.2).

Equilibrium approaches determine an optimal state (equilibrium) without explicitly determining individual choice behaviour. In fact, there may exist many different sorts of individual behaviour that yield the same equilibrium. Now, if one is interested in the effects of information, individual behaviours are indispensable, so these approaches cannot be used. Thus, it is not possible to say how wrong traditional models are as tools to estimate the effects of information. It suffices to say that they cannot deal with information. Still, it is important to understand what the differences are between the states which are determined by an equilibrium approach and those determined by the approach we adopted. We will try to answer this question next.
Suppose that the state of the traffic system $S_t$ is determined by an equilibrium approach. Such an approach implies some behaviour $B_t$. Although $B_t$ is not necessarily unique, it is consistent with $S_t$.

In the modelling approach we adopted it was shown that habit is crucial in the choice process. This means that in $B_t$ prior behaviours play an important role. Initially no habit exists. E.g. $B_2$ depends almost entirely on $S_t$ and initial expectations. For the first number of choices this observation holds. However, when habit is built up the states of the network become less important, and habit starts to dominate the choice process. It must be remembered that at this point habit is a consequence of 'early' states of the transport system. This means that in our modelling approach current choice behaviour and former states are strongly related. In the traditional equilibrium approach however, current choice behaviour and former states are independent; in fact former states are not mentioned in traditional equilibrium approach. This implies, that in situations in which former states are clearly different from the current state as determined by the equilibrium, the route choice behaviour implied by both approaches will differ. This is for instance the case when there is a trend in the $S_t$'s. An example may further clarify this argument.

Consider a two link network, with one origin, one destination, and each link connecting these two. Further consider an 'old' situation where one link was always congested and the other was not, and a 'new' situation in which due to altered infrastructure both links are congested. In that case the state resulting from the equilibrium approach will differ from the state resulting from our approach. In our approach the prior congested link will be used by more drivers than the equilibrium approach shows.

Although it is possible to demonstrate that the results of equilibrium approaches are sometimes wrong, it is not possible to make a general statement about the
size of the error, or whether equilibrium approaches are prone to overestimate or underestimate the actual state of the traffic system.

Also some results of the RIA field study demonstrate that the approach we have presented is better than the equilibrium approach. The argument for this is as follows. The choice behaviour during the last wave of the RIA study relates more to the equilibrium approach than the behaviour during the first wave, because during the first wave choice behaviour was almost completely dominated by habit, and during the last wave habit had diminished somewhat (remember that in equilibrium approaches habit does not exist). When we tried to simulate the behaviour during the first wave with parameters from the last wave a significantly worse model fit resulted.

In general it can be concluded that the model we presented is better than traditional models because habit turns out to be a major factor and traditional models do not deal with habit.

**What about traffic information?**

On the actual impact of traffic information on route choice a number of conclusions can be drawn. First of all, traffic information provision has clear and positive effects on the route choices of drivers. In the two empirical studies we carried out we demonstrated that information aids drivers to minimize the travel time or queues they experience.

Information also reduces the uncertainty about the outcome of choices. Uncertainty is often modelled as variance. Existing model studies have assumed that information would reduce variance. Our study shows that this assumption is correct. However, this is certainly not the only effect of information.

Information also induces 'more' learning from the same situation. This means that when information is provided, drivers take the outcomes of their most recent choices more into account, than when no information is provided. If no information is provided drivers rely more on general expectations based on prior experiences.

Another finding is that provision of 'bad' or unreliable information is not as dramatic as is often thought. Results demonstrate that in situations in which drivers are uncertain about outcomes, they respond to unreliable prescriptive information by decreasing their compliance. However, when information becomes reliable again, drivers need only a few good experiences to acknowledge this, and increase their compliance to previous high levels.

In general it may be concluded that, in the long run, information provision will never lead to unwanted effects for the traffic system, however unreliable the information provided may be. Even an information system that provides the wrong information constantly will not lead to adverse effects because drivers will eventually dismiss such an information source. Obviously, a system that provides bad information may have severe implications in the short run.
Of course, more reliable information will have the largest impact. On the whole this means, that, in the long run, information systems are always potentially effective traffic management tools.

When we try to integrate the results from both empirical studies, some paradoxical conclusions emerge. In unfamiliar and unpredictable environments such as in the laboratory experiments, utility maximization is larger than in well-known situations such as in the RIA panel study. At the same time a decrease in uncertainty resulting from information provision, leads to decreased habit strength (Table 9.1).

**Table 9.1** Weights of habit and outcomes of recent experiences in the choice process for different choice situations.

<table>
<thead>
<tr>
<th></th>
<th>habit</th>
<th>recent experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>unfamiliar choice situation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(laboratory experiments)</td>
<td>no information</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>with information</td>
<td>0.98</td>
</tr>
<tr>
<td>familiar choice situation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(field studies)</td>
<td>no information</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>with information</td>
<td>0.88 - 0.89</td>
</tr>
</tbody>
</table>

The general conclusion from Table 9.1 is that information provision leads to increased weight of the most recent experience within the choice process, irrespective of the familiarity of the drivers with the choice situation and the type of information provided.

The methodology that was developed focuses on the impact of traffic information on individual travel behaviour. With a proper loading technique the behaviour of all individuals can be translated to an aggregate level, e.g. traffic flows. Our present study does not provide the answer to what information strategy would be best in a specific environment. Only the integration of our model with a loading technique provides an instrument to assess different information strategies for a given network. Still, our research seems to indicate the following:
- On motorways, when information is provided on a collective level, e.g. road side information, provision of descriptive information is the best strategy, because drivers can evaluate this information immediately. Also prescriptive information, e.g guidance, can be applied. However, individually provided prescriptive information will only have beneficial effects if the penetration rate is low, or if the information system provides advice to individual drivers contingent on their compliance with the advice.
This can be explained as follows: we found credibility of and therefore compliance with prescriptive information to be very high. If prescriptive information is provided at a collective level, this can have a large impact on route convergence, i.e. many vehicles will be directed to a single route. In general few routes will have the capacity to carry this much traffic, so in that case prescriptive information will have adverse effects. Therefore, on motorways it is recommendable to provide descriptive information, and allow individuals to make a trade-off between alternatives. When descriptive information is provided, convergence in route choice will not be as dramatic as when prescriptive information is provided.

- In a city, prescriptive information seems likely to be superior to descriptive information. The reason for this is twofold. First, since city networks are more complex than motorway networks, descriptive messages are relevant to a smaller proportion of the car drivers. Second, descriptive information requires more cognitive processing than prescriptive information. Prescriptive information requires only compliance of drivers.

**What about habit?**

Habit has a clear functionality in choice behaviour: it reduces the task load of drivers and allows them to direct attention to more demanding tasks. Also, habit may be an efficient choice strategy when outcomes of options fluctuate strongly, but unpredictably, from day to day. However, under gradually, but systematically changing circumstances habit can lead to inadequate route choice, because drivers will stick to routines which are no longer efficient.

It may be felt that the strength of habit in the choice process might impose serious constraints on what can be achieved with traffic information. This is not a view we share. In this study it was shown that habit decreases when (descriptive) information is provided to drivers. Decreased habit strength allows for the use of both externally provided information and for better processing of (internal) expectations about outcomes.

### 9.4 Model Specification: Remaining Questions

The previous sections showed that not all questions concerning the research goals have been answered.

The algorithm generating route choice sets was not validated in this study. The main reason for this is that the validation studies concerned choices between two routes. It was not valid to assume that some drivers were unaware of one of these routes: in both laboratory experiments both routes were explicitly introduced to the subjects, and in the field study drivers were already very familiar with the choice situation.
The model on departure time choice has not yet been validated. The primary reason for this is that no dynamic data were available on departure times for trips for which pre-trip departure time information was provided.

Despite the above shortcomings it was concluded that the model is sufficiently comprehensive. Still a number of questions concerning its specification and behavioural foundation remain. Most of these questions can only be answered from new research. A few of these questions require special attention here, because neither the model specification, nor the validation thus far have made the difficulties underlying these questions clear.

A first issue is the way in which knowledge about the structure of the network must be specified. As is done in this model, the number of routes is assumed to be fixed. Only external information can enlarge this number. It can be argued that this is an oversimplification. It may be that individuals have both an active and a passive set of alternatives. In situations which are within the range of normal expectations the active set of knowledge may be addressed to determine route alternatives. The passively known network can be a superset of the actively known network. Only when something special happens, e.g. a major accident, would the passive set become active. In normal situations the passive set would not be addressed to determine route alternatives. This would imply two levels of knowledge on structure. It seems worthwhile to investigate further whether these two levels of knowledge on structure exist.

Although the model provides concepts for how drivers deal with information, the actual problems concerning dynamic information processing are far more difficult than we apprehended. In reality drivers will probably become faced with combinations of descriptive and prescriptive information. For instance, they may have access to an in-car route guidance system and also see queue length information on a variable message sign. At present it is not clear how simultaneous processing of different types of information can be modelled. An even more difficult and important question is how drivers deal with two conflicting sources of traffic information. The credibility of information will probably play a decisive role in this, and may be a way to start solving this problem.

Another remaining question is how drivers deal with descriptive information about unknown routes. Such information will increase the knowledge of the structure of the network. The problem that arises is that the present model specification requires initial expectations for all routes. However, it is unclear how initial expectations for unknown routes come about.

In the present formulation of the model drivers in environments in which no information is provided, are assumed to be ignorant of other information sources than their own experience. However, the way in which initial expectations about route performance were computed from aggregate experiences assumes dissemination of expectations between drivers. Once the model starts generating individual expectations dissemination of these expectations by other than high-tech
information systems (e.g. person-to-person, from magazines etc.) is not included in the model. It seems questionable that without provision of information from external information systems, drivers only learn from their own experience. Nevertheless, it must be said that, although on theoretical grounds other types of information dissemination should be included in the model, the validation of the model on the RIA-data did not indicate that this is necessary. The evidence for this is the good fit of the models we estimated. Of course, this does not demonstrate that it will not be necessary to account for other types of information dissemination at all.

The importance of the initial values problem, i.e. what do drivers expect when they make their 'first' choice and how habitual are they, has been addressed in this thesis. The first tests of the route choice model showed that model results may be quite sensitive to different initial values (see also discussion on initial values in Section 8.3). We think that this problem cannot be solved in a general way. This is one of the problems all dynamic models have to deal with on an ad hoc basis. For our particular tests of the route choice model the assumptions we made about initial values turned out to be adequate. So, although no general solution to the initial values problems is available, in practice, acceptable ad hoc solutions can be reached.

The model in a broader environment
The model was validated in a simple network, that consists of two non-overlapping routes. So all drivers were dealing with a binary choice environment, in which the perceived utility maximization rule could be modelled by a binary logit model. When using the model on a broader scale, a more complex choice environment will emerge. Because of overlapping routes the logit formula can no longer be adopted for such choice environments. In that case, a multinomial probit should be used, but it is well known that such choice models are very hard to estimate. A better way to proceed may be to carry out a number of studies on route choice in relatively simple networks, to arrive at prototypical sets of parameter values. Next, the appropriate set could be used to simulate route and departure time choice in more complex networks.

The structure of the knowledge was modelled by a known network. The network consists of links, and for all links expectations are retained. This means that through micro-simulation a proper route choice can be mimicked, using experiences and expectations for all links. Obviously, the habit decision rule remains route based, and the compliance rule is also not changed. Further, information processing is defined on a network level in a manner that can easily be applied in broader environments.

So we can conclude that the model is capable of dealing with larger networks, though a main problem will be estimation of the utility maximization parameters.
9.5 Recommendations for Future Research

To carry out studies to forecast the effects of traffic information (systems) on traffic flows in networks, two fundamental modules must be added to the choice model. Since it will not be possible to collect longitudinal panel data for all situations, dynamic Origin-Destination (O-D) data will be required. It is likely that in the near future such data will become available on a large scale, due to the implementation of monitoring techniques which are used by new information systems. An example is an individual route guidance system where the route of individual cars may be reconstructed from recording all locations where information exchange between the car and, for instance, road-side beacons took place.

When dynamic O-D data become available as input to the route and departure time choice models, the performance data necessary to run the choice models must be obtained from an adequate loading technique. Such techniques are currently being developed (see for instance De Romph, van Grol & Hamerslag, 1992). To start forecasting the influence of information systems on traffic flows, dynamic choice modelling and dynamic loading must be integrated into a single modelling tool. Also, the information system or information strategy itself must be integrated into the model. To use the model as a simulation tool to predict the effects of information systems in new environments, it will not be possible to use information made up by researchers as was done in the TNO laboratory experiments, or information as observed by drivers as in the field studies. This means that for instance congestion detection or incident detection systems must be integrated in the model.

For policy makers and transport authorities prediction of the effects of information provision is primarily interesting if it is possible to show what effects available information systems and strategies have on the traffic system. We feel that the integration of existing information systems into the model should be the next step in achieving the research goal more completely.

In what way does the distribution of expectations develop over different (groups of) drivers? This question has thus far not been addressed in this thesis but deserves some special attention here. In an experiment that was not reported in this thesis the model was used for simulations of choices between two routes in which performance was generated using the BPR-performance function\(^1\). Results from this experiment demonstrate that the distribution of expectations did not evolve in the way one would expect. Instead of a two variable normal like (bell-shaped) distribution a multinomial like distribution took shape. In this distribution distinct homogeneous groups could be identified with members

\(^1\)BPR-function \(t_a = t^0_a (1 + \frac{q_a}{C_a})^\beta\), with \(t_a\) travel time, \(t^0_a\) the free flow travel time, \(q_a\) the flow and \(C_a\) the capacity of link \(a\)
who had basically the same knowledge. This result suggests that (modelled) knowledge is distributed more discretely than one would expect. We have not pursued this line of experiments, because it might well be that the BPR-function is not suited to investigate the evolving distribution of expectations. However, for the future, research into this would be very interesting.

We will now turn to research which should be carried out in the near future to further develop the methodology proposed within this thesis.

To simulate the impact of information on route choice we need to gain more insight into the distribution of the familiarity of trips, and the relation between the familiarity of trips and the number of known routes. The distribution of trip purposes and distance may be related to this and a convenient way to model these implications.

To gain more insight into the decisional aspects of route choice, experiments on dynamic decision making seem necessary. We propose to perform an experiment in which subjects make choices on a day-to-day (or in general period-to-period) basis. Every time the whole group has made a route and departure time decision, a dynamic loading technique determines the individual implications (i.e. queues and travel times) of these decisions. Each individual would then be confronted with these implications and would make the next choice. This is basically the same experiment as was performed with the BGC participants, only in this case trip performance would not be fixed but would be dependent on the behaviour of the complete group of participants. This experimental setting can serve as the basis for numerous different experiments. Different information systems could be modelled and their impact could be investigated. By asking subjects about their expectations more insight into the learning model could be gained. The changes in habitual behaviour as a consequence of descriptive messages can be studied more thoroughly. Such research could truly benefit from experimental environments that can be provided by a driver simulator.
References


rijgedrag. TNO report IZF 1991 C-5, Soesterberg: Instituut voor Zintuigfysiologie TNO.


Mahmassani, H.S. & Herman, R. (1990) "Interactive experiments for the study of tripmaker behavior dynamics in congested commuting systems", in: Jones, P. (Ed.) Developments in Dynamics and Activity-Based Approaches to Travel Analysis, Avebury: Aldershot, p. 272-298.
References


Mathematical Preliminaries

Mathematical Prerequisites
Some background in graph theory is essential for reading this dissertation. This chapter provides a review of some of the more important background concepts, as well as a consistent set of definitions and notational conventions.

In addition to strictly mathematical background the reader should have some familiarity with the principles of computation. He should understand the concept of an algorithm, and how an algorithm is coded in machine language and executed by a computer. No serious attempt is made to explain these matters in this chapter or elsewhere in this dissertation. If the reader is unfamiliar with these concepts, he should consult a text on computer programming.

Sets and Relations
We assume that the reader is familiar with basic set operations and conventional set notation: ∈, ∉, ∼, ∪, ∩, ⊆, ⊇, ⊂, ⊃, ∅, etc. We write $T \subset S$ is $S$ is a proper subset of $T$, i.e. $T \subset S$ but $T \neq S$. We use braces {,} to indicate a set, and parentheses (,) to indicate an ordered set or sequence. For notational convenience we use "+" and "+" as follows:

$S + e = S \cup \{e\}$ and $S - e = S \setminus \{e\}$

The symmetric difference of two sets is indicated by the symbol $\oplus$, i.e., $T \oplus S$ the set of all elements contained in $S$ or in $T$ but not in both. By an abuse of notation we occasionally apply set operations to ordered sets, as though they were unordered.

We let $|S|$ denote the number of elements in $S$, the cardinality of $S$. If $S$ is a finite set of numbers, $\min S$ (max $S$) denotes the numerically smallest (largest)
element in $S$. By definition $\min \emptyset = +\infty$ and $\max \emptyset = -\infty$. Alternative notations for $\min A$, where $A = \{a_1, a_2, \ldots, a_n\}$ are

$\min \{a_i \mid 1 \leq i \leq n\}$

or $\min_{1 \leq i \leq n} \{a_i\}$ or simply $\min_i a_i$

where the range of $i$ is understood from the context.

**Digraphs, Subgraphs and Connectivity**

A directed graph or digraph $D$ is a structure $(N(D), L(D))$ consisting of a finite, non-empty set $N(D)$ of elements called nodes and a set $L(D)$ of ordered pairs of nodes called links. A link from node $i$ to node $j$ is denoted by $(i, j)$. If there is a link $(i, j)$ we say that node $i$ is adjacent to node $j$ and node $j$ is adjacent from node $i$ and that link $(i, j)$ is incident from node $i$ and incident to node $j$.

A digraph $D'$ is a sub-digraph of $D$ if $N(D') \subseteq N(D)$ and $L(D') \subseteq L(D)$.

If $N' \subseteq N(D)$ the subdigraph of $D$ induced by $N'$ has node set $N'$ and all links $(i, j)$ of $L$ such that both $i$ and $j$ are in $N'$.

A directed path between $o$ and $d$, or simply an $(o, d)$ path is a sequence of links from $o$ to $d$, where the $p$th link is incident to the same node from which the $(p+1)$th link is incident. The path is called acyclic if no two links are incident to the same node, or from the same node. We shall often drop the word "directed" from directed paths and so on.

A node $i$ is said to be connected to node $j$, and $j$ is said to be connected from $i$ if there exists an $(i, j)$ path. A digraph $G$ is said to be strongly connected if, for all pairs of nodes $i$ and $j$, $i$ is connected to $j$ and $j$ is connected to $i$.

**Definitions**

We consider for the definition of the model an environment of a road network $D$, an origin $o$, a destination $d$ and an individual $i$ who wants to travel from $o$ to $d$.

The network $D$ is a strongly connected digraph $(N(D), L(D))$. The assumption is that individual $i$ knows a subnetwork $D_i$, being a subdigraph of $D$.

An $(s, t)$ path with $s, t \in N(D)$ is called a path for all $s, t$. An acyclic $(o, d)$ path is called a route. Any path $p = (l_1, \ldots, l_n)$ in $D$ induces a subdigraph $D'$ with $N(D') = \{n \mid l \in p \text{ is incident from or to } n\}$ and $L(D') = p$.

Notation: $\lambda(p) = D'$.

For any set of paths $P = \{p_1, \ldots, p_n\}$ it holds that

$\lambda(P) = D'$, with $N(D') = \bigsqcup_i N(\lambda(p_i))$ and $L(D') = \bigsqcup_i L(\lambda(p_i))$. 

In $D$ for $R$, the set of routes is denoted by $\Lambda(D) = R$. Thus $R$ contains all $(o,d)$ paths. Now we will assume that for any set of routes $R$ it holds that $\Lambda(\lambda(R)) = R$. (in general $\Lambda(\lambda(P)) \neq P$). This assumption means that we will consider only clever individuals $i$, namely suppose $i$ knows two routes $r_1$ and $r_2$. The assumption implies that $i$ also knows any route that can be constructed out of $r_1$ and $r_2$. 
For wave $w$ the log-likelihood function can be derived as

$$\mathcal{L}_w = \sum_{i} \sum_{r=(w-1)\cdot15+1}^{w\cdot15} \log(\prod_{r} (1 - \delta_{irr}) + \sum_{r} \delta_{irr} \cdot P_{irr})$$  \hspace{1cm} (A.1)

The term $\prod_r (1 - \delta_{irr})$ has to be added to make sure that on days where $i$ did not chose any of the routes there is no contribution to the likelihood. Necessary conditions for maximizing $\mathcal{L}_w$ are (Luenburger, 1984):

$$\frac{\partial \mathcal{L}_w}{\partial H} = 0 \quad \forall w \geq 1$$ \hspace{1cm} (A.2)

$$\frac{\partial \mathcal{L}_w}{\partial \gamma} = 0 \quad \forall w \geq 1$$ \hspace{1cm} (A.3)

$$\frac{\partial \mathcal{L}_w}{\partial \psi} = 0 \quad \forall w \geq 1$$ \hspace{1cm} (A.4)

$$\frac{\partial \mathcal{L}_w}{\partial \beta_1} = 0 \quad \forall w \geq 1$$ \hspace{1cm} (A.5)

$$\frac{\partial \mathcal{L}_w}{\partial \beta_2} = 0 \quad \forall w \geq 1$$ \hspace{1cm} (A.6)

$$\frac{\partial \mathcal{L}_w}{\partial \beta_3} = 0 \quad \forall w \geq 1$$ \hspace{1cm} (A.7)
We adopted a numerical procedure where all equations are solved sequentially until the derivatives are small enough. Since it is hard to determine the derivatives analytically, an approximation was used

\[
\frac{\partial L_w}{\partial x_j}(x) \approx \frac{L_w(x_1, \ldots, x_j + \varepsilon_j, \ldots, x_6) - L_w(x_1, \ldots, x_6)}{\varepsilon_j} \quad 1 \leq j \leq 6 \quad (A.8)
\]
for a sufficiently small \( \varepsilon_j \) and \( x_1 = H, x_2 = \gamma, x_3 = \psi, x_4 = \beta_1, x_5 = \beta_2 \) and \( x_6 = \beta_3 \).

Conditions (A.2) through (A.7) are not sufficient. They would be if the function as defined in (A.1) were concave. It cannot be proven that this is the case. Therefore the estimation procedure was repeated for many different initial values. Also by determining the likelihood and the gradient for parameter combinations that were generated by random draws, in no case it appeared that a local maximum was found.

For the root-finding procedure we used the standard *False Position* method (Ostrowski, 1966). This method will be referred to as FP and works as follows (Fig A.1):

![Figure A.1 False Position method for root-finding](image)

Suppose we want to determine the root \( x^* \) of the function \( f \) of \( x \). Initially we have two points, \( (x_1, f(x_1)) \) and \( (x_2, f(x_2)) \) such that \( f(x_1) < 0 \) and \( f(x_2) > 0 \). Obviously the root must lie somewhere between \( x_1 \) and \( x_2 \). Now \( f \) is
approximated by the straight line between $x_j$ and $x_2$. The root of this line, $i$ is the first approximation of $x^*$. Since $f(i) > 0$, $x_j$ becomes $i$ and $x^*$ obviously must lie between $x_j$ and $x_2$. Now $ii$ is the second approximation of $x^*$ and is the root of the line between $x_j$ and $x_5$. This procedure is repeated until the value of $f$ at an approximation of $x^*$ is sufficiently small.

Now the procedure for solving the system of equations (A.2) to (A.7) is as follows:

1 **Initialization**

$$x^0 = (H^0, \gamma^0, \psi^0, \beta_1^0, \beta_2^0, \beta_3^0)$$
$$k = 1$$

2 **Find Root**

Solve (A.2) using FP and (A.8) with $j = 1$ starting at $x^{k-1}$, record $x_j^k$ and set $x_j^{k-1} := x_j^k$

Solve (A.3) using FP and (A.8) with $j = 2$ starting at $x^{k-1}$, record $x_2^k$ and set $x_2^{k-1} := x_2^k$

Solve (A.4) using FP and (A.8) with $j = 3$ starting at $x^{k-1}$, record $x_3^k$ and set $x_3^{k-1} := x_3^k$

Solve (A.5) using FP and (A.8) with $j = 4$ starting at $x^{k-1}$, record $x_4^k$ and set $x_4^{k-1} := x_4^k$

Solve (A.6) using FP and (A.8) with $j = 5$ starting at $x^{k-1}$, record $x_5^k$ and set $x_5^{k-1} := x_5^k$

Solve (A.7) using FP and (A.8) with $j = 6$ starting at $x^{k-1}$, record $x_6^k$ and set $x_6^{k-1} := x_6^k$

Set $k := k + 1$

3 **Stop-criterium**

If $$\frac{\partial \mathcal{L}_w}{\partial x_j}(x^{k-1}) < \theta$$ then STOP else GOTO step 2
Algorithms for Static Deterministic and Stochastic User Equilibrium

Static Equilibrium Approaches

In order to be able to define the deterministic and stochastic static equilibria, first traffic assignment is defined as a mathematical program formulation (Sheffi, 1985). Both a network and an OD-matrix are used. Suppose each OD-pair \((o,d)\) is connected by a set of routes \(R\). Now let \(q_{o}^{rd}\) be the flow and \(tt_{r}\) the travel time from \(o\) to \(d\) along route \(r\) and \(tt_{a}\) is the travel time on link \(a\) \((r \in R)\). Then it holds that

\[
    tt_{r} = \sum_{a} tt_{a} \delta_{ar}
\]

\[\text{(B.1)}\]

where \(\delta_{a,r} = 1\) when link \(a\) is on route \(r\) and 0 otherwise.

Now the static deterministic user equilibrium, defining the situation where no user can improve his travel time by unilaterally changing route. This definition as first put forward by Wardrop (1952) assumes that each cardriver has complete and perfect knowledge of the network and wants to minimize his travel time. Now suppose that the OD-matrix \(T\) is given, with \(T_{o,d}\) indicating the number of trips from origin \(o\) to destination \(d\), then the solution of the static deterministic equilibrium can be obtained by solving
\[ \min z(x) := \sum_a x_a \int_0^{t_{od}(\omega)} dt_{od}(\omega) d\omega \]  \hspace{1cm} (B.2) 

subject to
\[ \sum_r q_r^{od} = T_{od} \]  \hspace{1cm} (B.3)
\[ q_r^{od} \geq 0 \]  \hspace{1cm} (B.4)
\[ x_a = \sum_{o,d,r} q_r^{od} \delta_{ar} \]  \hspace{1cm} (B.5)

The solution method of (3.2) s.t. (3.3) to (3.5) is

---

**Step 1**  \hspace{1cm} *(Initialization)*
Perform AON-assignment based on \( t_{od} = t_{od}(\theta) \) for all \( a \), yielding \( \{x_a^1\} \). Set \( n = 1 \)

**Step 2**  \hspace{1cm} *(Update travel times)*
Set \( t_{od}^n = t_{od}(x_{od}^n) \) for all \( a \)

**Step 3**  \hspace{1cm} *(Direction finding)*
Perform AON-assignment based on \( t_{od} = t_{od}(n) \) for all \( a \), yielding \( \{y_a^n\} \).

**Step 4**  \hspace{1cm} *(Line search)*
Solve \[ \min_{0 \leq \alpha_n \leq 1} \sum_a t_{od}(\omega) d\omega \] 

**Step 5**  \hspace{1cm} *(Update flows)*
Set \( x_{od}^{n+1} = x_{od}^n + \alpha_n (y_{od}^n - x_{od}^n) \) for all \( a \).

**Step 6**  \hspace{1cm} *(Convergence test)*
If convergence criterion is met, STOP, else \( n = n+1 \) and goto 1

---

From the formulation of the static deterministic user equilibrium (SDUE), the stochastic version can be formulated by not assuming that all tripmakers have a perfect knowledge of the network. Random choice models are used
for route choice.

Let $U_r$, represent the perceived travel cost on route $r$, connecting $o$ and $d$. Obviously $U_r$ is a random variable. Let further $t_r$ be the actual travel time on route $r$, connecting $o$ and $d$ and further let $\varepsilon_r$ be a random variable with mean 0. Assume as in random utility models that

$$U_r = t_r + \varepsilon_r$$  \hfill (B.6)

Thus travel cost is defined as travel time. The share of drivers choosing route $r$ is

$$P_r = \Pr \{U_r < U_s, \forall s \neq r\}$$  \hfill (B.7)

Nota Bene:

$$\Pr \{U_r = U_s\} = 0 \quad \forall r, s \text{ with } r \neq s$$  \hfill (B.8)

Dependent on the choice of the distribution of the random error term a specific choice model can be derived.

Now the static stochastic user equilibrium (SSUE) can be formulated as the solution of the following minimization program

$$\min z(x) = - \sum_{od} T_{od} \mathbb{E} \left[ \min_k \{ U_k \} \mid t_{k}(x) \right] + \sum_{d} x_d t_{d}(x_d) - \sum_{0}^{x_d} \int t_{a}(\omega) d\omega$$  \hfill (B.9)

subject to

(3.3) to (3.5) and

$$a_{od}^{\text{SSUE}} = P_{r}$$  \hfill (B.10)

With $P_r$ being the probability of choosing route $r$ when travelling from $o$ to $d$. The solution of this program is more simple than it’s formulation. Static

---

**Step 1  (Initialization)**

Perform stochastic network loading based on $t_a = t_a(0)$ for all $a$, yielding $\{x_a\}$. Set $n \leftarrow 1$

**Step 2  (Update travel times)**

Set $t_a^n = t_a(x_a^n)$ for all $a$

**Step 3  (Direction finding)**

Perform stochastic network loading based on $t_a = t_a(n)$ for all $a$, yielding $\{y_a^n\}$. 

So $y_a^n = \sum_{i,j} \sum_r T_{ij} P_r(U^n) \delta_{a,r}$, the share representing the random choice model.

**Step 4  (Flow update)**
Find new flow pattern by setting $x_{a}^{n+1} = x_{a}^n + \frac{1}{n} (y_{a}^n - x_{a}^n)$ $\forall a$

**Step 5  (Convergence test)**
If convergence criterion is met, STOP, else $n \leftarrow n+1$ and goto 1
Effects of Information using a Static Approach
Effectiveness of Information Systems in Networks With and Without Congestion

Rudi Hammerslag and Eric C. van Berkum

The use of road transport information (RTI) is a recent development that optimizes the use of existing facilities in the transportation system and serves three main goals: alleviation of congestion, diminution of air pollution, and reduction of incidents. RTI instruments deal with traffic information. Examples of RTI systems are pretrip planning, roadside displays, radio data system—traffic message channel, and in-car navigation. To model the effects of providing the road user with information a method is used in which stochastic and deterministic assignments were compared for both networks with and without congestion. To let information also affect destination choice and the spatial distribution of activities, the assignment models were combined with different distribution models. The amount of information that travelers have was translated to a "level of uncertainty" measure. The more informed a traveler is, the lower the level of uncertainty. Since the effects appeared to be network dependent, a number of different networks were examined. Simulations showed that the amount of kilometers driven decreases when travelers are provided with better and more information.

The use of road transport information (RTI) is a recent development that optimizes the use of existing facilities in the transportation system and serves three main goals: alleviation of congestion, diminution of air pollution, and reduction of incidents. RTI instruments deal with traffic information. Systems such as pretrip planning, roadside displays, radio data system—traffic message channel, and in-car navigation are all part of RTI. From a planner's viewpoint, it is essential to know the possible impact of RTI on the traffic system. One way to predict the effects of RTI is to model individual travel behavior and to incorporate information explicitly as a model component. In this way, the effect of information on travel behavior can be simulated. Before this can be done, however, it is necessary to model the current situation, in which the traveler is not perfectly informed and therefore makes nonoptimal choices.

In many existing models it is assumed that people have perfect knowledge of all travel alternatives. This assumption means that the usefulness of providing information to travelers cannot be determined. In the approach presented in this paper, the classic four-stage model is central. The key issue is, however, that the perceived travel times instead of the objective travel times are being used in all stages. Therefore, a measure of uncertainty is introduced. Uncertainty affects not only route choice, but also destination choice and the spatial distribution of activities. A further assumption is that information reduces uncertainty. So by using models in which route choice, distribution, or location of activities, or all three, are influenced by the (perceived) travel times and the outcomes for different levels of uncertainty are compared, it is possible to get an insight in the effects of information.

RELATED STUDIES

In recent years, many approaches have been presented to provide insight into the possible benefits of information systems in transport.

The feasibility of the Comprehensive Automobile Traffic Control project (1) was studied by using a simulation model in which the noninformed users choose their route on the basis of various factors, such as travel time, length of the route, number of lanes, number of turns, and so on, and the informed users choose their route solely on the basis of travel time. It was found that in Tokyo travel time could be reduced by 6 percent and fuel consumption by 5 percent. Tajiri et al. (2) investigated the effectiveness of a route guidance system by using a mathematical model. Among other factors, they used travel time reduction as a measure of effectiveness. The outcomes, however, must be related to the heavy assumptions under which the model is valid. The reduction in travel time was found to be 11 percent. van Vuren (3) tried to model the effectiveness of route guidance by using a multinomial class equilibrium and stating that the noninformed users behave greedily, as in a deterministic user equilibrium, whereas the informed users behave according to the principle of a system optimum. The results were found to be unrealistic because the uninformed users were better off.

Koutsopoulos and Lotan (4) modeled the impact of information on travelers by using a stochastic user equilibrium and stating that information systems reduce the variance in travel time. They found a reduction in travel time of about 5 percent, dependent on the noninformed users' reaction.

Muttamassani and Jayakrishnan (5) modeled the effectiveness of a real-time information system on a small test network with three parallel highways and a number of switching possibilities. The researchers chose one information supply strategy and focused on the users' reaction by defining them as bounded rational individuals. An important result was that the system performance might actually worsen by myopic local actions of the drivers. Van Berkum and van der Meulen (6) presented a dynamic approach that simulates rational, uncertain, persistent individuals who base their decisions on experience and have a limited knowledge of alternatives.

R. Hammerslag, Departments of Civil Engineering and of Mathematics and Informatics, Delft University of Technology, P.O. Box 5048, 2600 GA Delft, The Netherlands. E. C. van Berkum, Bureau Goudapil Coyling, P.O. Box 161, 7400 AD Deventer, The Netherlands.
The approach that is followed in this paper is an extension of the work of Koutsopoulos and Lotan (4). The situation of recurrent congestion was also studied in this research. But whereas Koutsopoulos and Lotan restricted the effects of better information to route choice, the impact on destination choice and the location of activities has also been studied here. Another difference is that the amount of uncertainty in their approach was initially too small. Further, they examined one network, whereas different networks are studied here. Because the results are network dependent, it is difficult to compare results, but the results they found on route choice are on the same order of magnitude as the results presented in this paper. The results gained from the present research are not comparable with the results found by Mahmoodani and Jayakrishnan. They studied the reaction of people on dynamic traffic information that reports the actual traffic conditions. When drivers react myopically, this information becomes invalid. An adjustment process will occur, which in the end will lead to an equilibrium. This equilibrium is focused on in this paper. This further implies that the information given to the drivers is in some sense not real-time information but rather future-time information.

MODELING APPROACH

General

The main hypothesis of this study is that the fact that people are uncertain about travel times on links has more effects than only on route choice. There will also be effects on destination choice as well as on the spatial distribution of activities. People make trips because they want to perform activities that are spatially separated. In the traditional four-stage models, the spatial distribution of activities is fixed. In this study models are used that include the spatial distribution of activities as endogenous. Users choose a route by minimizing some measure of cost. In this study travel time will only be used as cost. Travelers do not possess perfect information about the network they travel on. This means that people do not minimize the objective time but rather the perceived travel time.

Destination choice can also be modeled by using a cost minimization procedure (8). Because of the observation made previously, this means that in determining the origin-destination (O-D) flows, the perceived cost or travel time must also be used. A basic assumption here is that route choice is made on the basis of the same perceived travel times as destination chosen and the location of activities are made. Traffic information affects the perception of travel times in the network. The perceived travel times will be modeled as stochastic variables whose distribution is influenced by the amount of available information.

The approach that has been followed uses the traditional four-stage model as a basis, although an adjusted form has been developed. The following assumptions are therefore needed:

- All people base their decisions on what they know; and
- People base their route and destination decisions on the same perceived travel time.

In order to make the approach not too complex the following limitations have been adopted:

- The total number of trips is constant under all levels of uncertainty;
- All people have access to the same level of information;
- Information is assumed to be good and true; and
- No distinction has been made between different modes and purposes.

Route Choice

Link travel times on the network are defined as stochastic variables. The variance in travel times—that travel times are unpredictable to a certain extent—may be understood as uncertainty of travelers. Consequently, users will have different perceptions of travel times on the links.

A deterministic user equilibrium (DUE) can be defined as the situation in which no traveler can improve his or her travel time by unilaterally changing route (9). This definition assumes that every traveler has an exact knowledge of travel times and flows on all links in the network. A stochastic user equilibrium (SUE) can be defined as the situation in which every traveler thinks that he or she cannot improve the travel time by unilaterally changing routes (9,10). This definition assumes that travelers have different perceptions of travel times. Comparing a SUE with a DUE enables estimating the effect of providing information to travelers (or reducing their uncertainty) on the traffic system (4,11). Because this comparison can be translated as comparing travelers with exact knowledge of all travel times in the network with travelers with different perceptions of travel times in the network.

In networks without congestion the DUE assignment becomes a simple all-or-nothing assignment, where the SUE assignment becomes a classic stochastic assignment (12,13). The impedance of a link on a network for person p is a function of a number of variables $X_{a}$ such as time, cost, and distance and their relative importance $b_i$ plus some measure of uncertainty. We define

$$Z_{w} = \sum B_i \cdot X_{a} + e_{w}$$

(1)

where $e_{w}$ is a noise term. The resulting route choice model depends on the distribution of $e_{w}$. It is supposed that $e_{w}$ is normally distributed with mean 0 (13), which yields a probit model for route choice. The introduction of the noise term $e_{w}$ can be explained by stating that (a) behavior cannot completely be explained by all $X_{a}$'s, (b) individuals have different perceptions of the $X_{a}$'s and their relative importance therefore may differ, and (c) individuals are uncertain about the exact value of the $X_{a}$'s, especially because these values differ in time. Instead of impedance, generalized cost, or generalized time only travel time will be considered as a measure for deterrence in this study.

The travel time on a link $a$ in a network without congestion is

$$Z_a = Z_0 + \alpha \cdot R \cdot \sqrt{Z}$$

(2)
where

\[ Z_a = \text{mean travel time of link } a, \]
\[ R = \text{draw from a normal } N(0,1) \text{ distribution, and} \]
\[ a = \text{factor determining the variance (from now on will be called level of uncertainty).} \]

The value of \( a \) is dependent on the chosen dimension (14). Given an O-D matrix, \( a \) can be determined by comparing true with model flows. When the dimension is minutes, it has been estimated that \( 0.5 < a < 1 \) for a regional network with relatively low alternative routes (13). Furthermore, Boyz (14) developed an efficient methodology for estimating \( a \) from observed flows.

In reality the uncertainty will, among other things, be a function of the frequency with which a person travels between a certain O-D pair. The lower the frequency, the higher the uncertainty. In this study, the uncertainty is assumed to be equal for all travelers.

The travel time of a link in a network with congestion is

\[ T_a = T_a + q_a \cdot R \cdot \sqrt{Z_a} \quad \text{(3)} \]

with

\[ Z_a = \left( 1 + \frac{q_a}{c_a} \right) \quad \text{(4)} \]

where

\( Z_a \) = the mean travel time of link \( a, \)
\( q_a \) = the flow on link \( a, \)
\( c_a \) = the capacity of link \( a, \)
\( R \) = a draw from a normal \( N(0,1) \) distribution,
\( a \) = the level of uncertainty, and
\( \tau \) = a parameter dependent on the definition of capacity.

**Destination Choice and the Location of Activities**

Because the distribution process is a utility maximization process (or disutility minimization), information will also have impact on destination choice resulting in a distribution of flows and the location of activities. In this study, the following interaction model with elastic constraints is used (15):

\[ \min \sum \left( \sum T_i - m_i \cdot \cdot \cdot A_j \right) - \sum \left( \sum T_i - l_i \cdot D \right) \quad \text{(5)} \]

Subject to

\[ T_i = 6(m_i Q_i x_i \exp[-0.4 \ln(Z_o - d_o + 1)]) \quad \text{(6)} \]

where

\( T_i \) = number of trips between \( i \) and \( j, \)
\( m_i \) = equilibrium factors,
\( Q_i \) = polarties,
\( x_i \) = objective travel time between \( i \) and \( j, \)
\( A_i, d_i \) = arrivals and departures, and
\( d_o \) = difference between objective and perceived travel time between zones \( i \) and \( j. \)

In solving the model, the terms \( l(1 + g) \) and \( l(1 + h) \) become important. These terms will be called elasticities. Thus when \( g \) and \( h \) are both 0 the elasticities become 1 and the model turns into the classic gravity model with fixed constraints. To coordinate spatial planning, transportation development, and spatial development, the model with elastic constraints was developed. The value of the equilibrium factors in Equation 6 is a function of the extra effort needed to comply with the constraints. In poorly accessible areas, the value is high and, inversely, in easily accessible areas the value is as dependent, though not exclusively, on the accessibility, the objectives in Equation 5 must become elastic.

**Combining the Assignment and the Distribution Model**

To determine the effects of information on route choice, route and/or destination choice, and/or the location of activities, the following models must be compared:

- In the case of no congestion, a distribution model with and without elastic constraints will be compared with the same model but combined with a stochastic break assignment.
- In the case of congestion, first the DUE assignment will be combined with the distribution model without (10.17) and with elastic constraints (16). Second, the same combination will be made, but with the SUE assignment.

To combine a SUE assignment with a distribution model, including the assumption that both models deal with the same perceived travel times, it is necessary to determine how the perceived travel times must be used in the distribution stage. In the proposed distribution model there is one value for travel time between each O-D pair. In reality this travel time is different for every individual (perceived travel time). Starting with \( Z_{opt} \) the perceived travel time between \( i \) and \( j \) along route \( r \) of person \( p \), person \( p \) chooses that route with the smallest perceived travel time. Therefore, it holds that

\[ Z_{opt} = \min Z_{opt} \quad \text{(7)} \]

Suppose the population \( B \) is divided in two groups, B1 and B2. Persons belonging to B1 find route \( j \) the best and persons belonging to B2 do not, so

\[ Z_{opt} > Z_{opt} \quad \forall p \in B1 \text{ and } r \neq j \quad \text{(8)} \]

For persons belonging to B2 it holds that

\[ Z_{opt} = Z_{opt} \quad \forall p \in B2 \quad \text{(9)} \]

So

\[ Z_{opt} > Z_{opt} \quad \forall p \in (B1 \cup B2) \quad \text{(10)} \]

Suppose there are \( N \) persons in B, then

\[ Z_o = \frac{1}{N} \sum Z_{opt} \text{ and } Z_{opt} = \frac{1}{N} \sum Z_{opt} \quad \text{(10.1)} \]
Using Equation 10 it holds that

$$Z_i = Z_{i0}$$

(10.2)

The same result can be derived for every route r, so

$$Z_r = Z_{r0} \quad \forall r$$

(11)

Thus the perceived travel time between any O-D pair sent in the distribution stage is always less than or equal to the perceived travel time of any of the chosen routes between the O-D pair.

The difference between the best route and the travel time between an O-D pair is dependent on the network. When, for instance, one route is by far the best so that every traveler between that O-D pair will choose that route, the equal sign in Equation 11 holds for this particular route. When there is a spreading over the routes for all r the less than sign will hold. When the level of uncertainty α becomes larger, the spreading in routes becomes larger and $Z_r$ will decrease; or in other words the difference between model travel time and the mean perceived travel time of the objectively seen best route (which is by definition the objective travel time of the best route) becomes larger. So in the distribution stage the following travel time is used:

$$Z_i = d_{i0}$$

Where $Z_i$ is the mean perceived travel time of the objectively seen best route between zone $i$ and $j$; $d_{i0}$ is an increasing function of $\alpha$ (obviously when $\alpha = 0$, also $d_{i0} = 0$).

**Models and Algorithms**

To study the effects of more or better information on route choice the "A model" is used, which is a stochastic equilibrium assignment with a given, fixed O-D matrix. To study the effects on destination choice and on the resulting O-D flows too, the "A + D model" is used. In this model, a stochastic equilibrium assignment and distribution with fixed constraints are combined. In the O-D matrix, the numbers of departures and arrivals are fixed for each zone. The cell volumes solve Equation 5 subject to Equation 6 with $g = h = 0$.

To study the effects of activities on the locations, the "A + D + L model" is used. In this model, a stochastic equilibrium assignment and distribution with elastic constraints are combined. In the O-D matrix, the numbers of departures and arrivals are variable for each zone, but the total number of trips is fixed. The cell volumes solve Equation 5 subject to Equation 6 with $g$ and $h$ not necessarily equal 0.

In Figures 1 through 4, the separate algorithms for the congestion situation are depicted. Basically, the methodology as proposed by Evans (17) is followed. The steps that have to be executed more than once because the draw must take place $n$ times have been depicted with a thick line. In the case of no congestion, the step where new travel times are computed becomes trivial.

A generalized description of the used algorithm is

1. Read network;
2. Draw link travel times for every link;
3. Determine travel times from shortest routes between every O-D pair;
4. Repeat No. 2 and No. 3 $n$ times;
5. IF model = A THEN
   read O-D matrix
   ELSE determine mean travel times with the travel times per draw determined in No. 3. Determine O-D matrix with elastic constraints (A + D + L) or with fixed constraints (A + D) using a Gauss-Seidel iteration procedure to solve Equation 5 subject to Equation 6.

![Figure 1: A model, congestion.](image-url)
FIGURE 2  A + D model, congestion.

FIGURE 3  A + D + L model, congestion.

Entity that is exogenous in the model

Entity that is endogenous in the model

The thick arrow means that it must be performed several times, i.e. twice by each draw.

FIGURE 4  Explanation for Figures 1 to 3.
6. Subdivide the O-D matrix in \( m \) equal parts and load them to the routes determined in No. 3, yielding loads \( q_i^k \) for link \( L_k \).

7. Load link \( u \) in iteration \( r \) the network with \( q_i^r = [q_i^{r-i} (i - 1) + q_i^r] / r \).

8. In case of congested networks: determine new travel times, and

9. Go to No. 2 until stop criterion is reached.

EXPERIMENTS

The experiments were performed using the research facilities of the Teacher Friendly Transportation Programs V0.1 (19). In the stochastic assignments \( m \), the number of draws was 4 and the number of iterations was 8. Because for every tree of shortest paths, new travel times were drawn, the total number of draws is 32 times the number of zones. Convergence was no problem in all test networks. The number of iterations was far less than expected in a combined distribution-assignment procedure (10, 20).

Networks

Earlier it was observed that the spreading of chosen routes determines to some extent the value of \( d_c \). The amount of spread is not only dependent on the size of the variance as used in the stochastic assignments, but also on the presence of (relevant) alternative routes. Obviously in a situation in which there are hardly any alternative routes, the spread will be small. Therefore it is important to investigate different networks. In this study four regional networks with a diameter of about 40 km (called REGIO, RING, SLOW, and CBD) and one urban network with a diameter of about 15 km (TOWN) were examined. For the regional networks only, the situation without congestion is considered. For the urban network both the situation with and without congestion are considered.

In Figures 5 to 7 some of the networks with their spreading of activities and flows are shown. In Figure 8 the notation of the activities is shown. The networks RING, SLOW, and FAST are the same size (number of links, number of nodes, distances) as CBD.

\[
\text{FIGURE 5 Network CBD.}
\]

\[
\text{FIGURE 6 Network REGIO.}
\]

\[
\text{FIGURE 7 Network TOWN.}
\]

\[
\text{FIGURE 8 Notation of activities.}
\]

In Figure 8 the radius of the outer circle is proportional to

\[
\max \left( \sum \tau_c, \sum \tau_i \right)^{1/2}
\]

The radius of the inner circle is proportional to

\[
\left| \sum \tau_c - \sum \tau_i \right|^{1/2}
\]
CONCLUSION

Trips and activities are a result of decisions people make. These decisions concern route and destination choice as well as activity choice. The actual choices depend on the perceived travel times, rather than on the objective travel times. As a result, travelers think they choose the best route, but this route is not necessarily the best from an objective point of view. Also destinations are chosen because they appear to be close. This causes extra, unnecessary carkilometers.

The approach presented in this paper has a number of assumptions and limitations about information:

- Information is seen as an abstract entity; it is not possible to evaluate a specific information system or different types of information.
- Because of the equilibrium approach the presented method is able to predict the long-term effects of the provision of information in a situation of recurrent congestion.

The results of this study should be looked at in light of these assumptions as well as in light of the limitations this approach has.

It was proven that the perception of two or more independent routes is always less than or equal to the perception of each of two or more routes together. The travel time of the chosen route is systematically being underestimated. Providing information reduces the difference between perceived travel time and objective travel time. This has an impact on the choice of route, destination, and activity. As a result, the amount of carkilometers decreases. The different test cases show that the form of the network, with respect to the presence of alternative routes, is of importance. Further, the simulations show that in a situation with congestion, the decrease of carkilometers is larger than in the situation with no congestion. Currently it is not possible to quantify the effects of information precisely because the present and future values of α are not exactly known, uncertainty will only partially be influenced by information, and only a part of the travelers will use the information. On the other hand, through route guidance, delays on intersections may be minimized (21) and the influence that information about incidents could have is neglected. With the above considerations in mind it seems valid to state that information systems may decrease the amount of carkilometers in urban networks by 15 to 20 percent and in regional networks by 5 to 10 percent.

REFERENCES


The inner circle is open when
\[ \sum_{\gamma} r_{\gamma} < \sum_{\gamma} r_{\gamma} \]  \hspace{1cm} (14)

The description of the networks is as follows:
- CBD — network with speedways (100 km/h) to a central area; other roads are 40 km/h.
- FAST — network with only speedways (100 km/h).
- REGHD — network like "CBD" but more dense near the center.
- RING — network with speedways in a ring around a central area.
- SLOW — network with only secondary roads of 40 km/h.
- TOWN — urban network; there are no trips to or from the surrounding areas.

Level of Uncertainty, \( \alpha \)

The simulations have been performed for all networks with levels of uncertainty \( \alpha = 0.0, \alpha = 0.5, \) and \( \alpha = 1.0. \) For the network TOWN \( \alpha = 0.3 \) and \( \alpha = 0.8 \) were also taken into account.

Results

The results of the simulations for the urban network with and without congestion are given in Tables 1 and 2. Results for the regional networks without congestion are given in Tables 3, 4, and 5. For all networks, the amount of car-kilometers (vehicle miles) increases when the level of uncertainty increases. Because provision of information can be translated in a smaller level of uncertainty, it can be stated that providing road users with information reduces the amount of car-kilometers. The results show that the gains differ per network. A network means not only the set of links and nodes, but also the initial trinets. This observation implies that it is hard to compare the results of other studies with one another and with these results, because different networks are used in all studies.

The results for the networks as listed in Tables 3, 4, and 5 are more or less comparable. These results were calculated with models that did not deal with congestion. The results for the TOWN network show a larger increase in car-kilometers when \( \alpha \) increases (See Table 2). This can be explained by the fact that the TOWN network obviously contains more alternative routes than all the other networks. The spread in route choice will be bigger for this network since there simply exist more alternatives. Because the network outcomes in Tables 3 to 5 reflect few alternative routes, the effect on route choice is small compared with the effect on destination choice (compare the outcomes in Tables 3 and 4). The extra-effect on the location of activities is also small compared with the effect on destination choice (compare the outcomes in Tables 4 and 5).

When looking at the network TOWN, the effects on route choice are the largest. Change in destination choice and in the location of activities are marginal compared with this effect. Because this network is more realistic than the other ones, this observation may be generally true. By comparing Tables 1 and 2, it follows that the effect of the provision of information is larger in the network with congestion than without congestion.

**TABLE 1** CAR-KILOMETERS FOR TOWN NETWORK, WITHOUT CONGESTION, UNDER DIFFERENT LEVELS OF UNCERTAINTY (KM FOR \( \alpha = 0.0 \) ARE 0)

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>A</th>
<th>A+D</th>
<th>A+D+L</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>117</td>
<td>129</td>
<td>136</td>
</tr>
<tr>
<td>0.7</td>
<td>122</td>
<td>133</td>
<td>140</td>
</tr>
<tr>
<td>0.5</td>
<td>104</td>
<td>117</td>
<td>123</td>
</tr>
<tr>
<td>0.3</td>
<td>107</td>
<td>120</td>
<td>123</td>
</tr>
<tr>
<td>0.0</td>
<td>100</td>
<td>110</td>
<td>110</td>
</tr>
</tbody>
</table>

**TABLE 2** CAR-KILOMETERS FOR TOWN NETWORK, WITH CONGESTION, UNDER DIFFERENT LEVELS OF UNCERTAINTY (KM FOR \( \alpha = 0.0 \) ARE 0)

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>A</th>
<th>A+D</th>
<th>A+D+L</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>124</td>
<td>129</td>
<td>136</td>
</tr>
<tr>
<td>0.7</td>
<td>114</td>
<td>121</td>
<td>126</td>
</tr>
<tr>
<td>0.5</td>
<td>106</td>
<td>110</td>
<td>113</td>
</tr>
<tr>
<td>0.3</td>
<td>101</td>
<td>105</td>
<td>108</td>
</tr>
<tr>
<td>0.0</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

**TABLE 3** CAR-KILOMETERS DRIVEN FOR DIFFERENT NETWORKS, UNDER DIFFERENT LEVELS OF UNCERTAINTY WITH THE A-MODEL (KM FOR \( \alpha = 0.0 \) ARE 0)

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>CBD</th>
<th>RING</th>
<th>SLOW</th>
<th>FAST</th>
<th>RAGHD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>102</td>
<td>102</td>
<td>102</td>
<td>102</td>
<td>102</td>
</tr>
<tr>
<td>0.5</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>0.2</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

**TABLE 4** CAR-KILOMETERS Driven FOR DIFFERENT NETWORKS, UNDER DIFFERENT LEVELS OF UNCERTAINTY WITH THE A+D-Model (KM FOR \( \alpha = 0.0 \) ARE 0)

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>CBD</th>
<th>RING</th>
<th>SLOW</th>
<th>FAST</th>
<th>RAGHD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>104</td>
<td>104</td>
<td>104</td>
<td>104</td>
<td>104</td>
</tr>
<tr>
<td>0.5</td>
<td>102</td>
<td>102</td>
<td>102</td>
<td>102</td>
<td>102</td>
</tr>
<tr>
<td>0.2</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

**TABLE 5** CAR-KILOMETERS DRIVEN FOR DIFFERENT NETWORKS, UNDER DIFFERENT LEVELS OF UNCERTAINTY WITH THE A+D+L-Model (KM FOR \( \alpha = 0.0 \) ARE 0)

<table>
<thead>
<tr>
<th>( \alpha )</th>
<th>CBD</th>
<th>RING</th>
<th>SLOW</th>
<th>FAST</th>
<th>RAGHD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>117</td>
<td>117</td>
<td>117</td>
<td>117</td>
<td>117</td>
</tr>
<tr>
<td>0.5</td>
<td>101</td>
<td>101</td>
<td>101</td>
<td>101</td>
<td>101</td>
</tr>
<tr>
<td>0.2</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>
Sensitivity Tests

Parameter used:

\[
\begin{align*}
\beta_1 & = -9.6 \\
\beta_2 & = -0.14 \\
\beta_3 & = 0.6 \\
\psi & = 0.5
\end{align*}
\]

Initial travel times were 30 minutes for both routes, standard deviation was set to 0 and initial cost was also 0.

These parameters were estimated using a reformulation of the model where only utility maximization was involved (Van der Mede and Van Berkum, 1992). Monte-Carlo simulations were performed with different sets of parameters for habit as denoted in Table D.1.

In Table D.2 similar benchmarks as put forward in Chapter 8 were determined. In Figures D.1 through D.19 the simulation results and the observed results for route choice proportions are compared.
Table D.1 The 19 sets of habit parameters that were used

| set | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  | 16  | 17  | 18  | 19  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| $H_{max}$ | 0.0 | 0.9 | 0.5 | 0.9 | 0.5 | 0.9 | 0.5 | 0.9 | 0.9 | 0.5 | 0.9 | 0.5 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.5 |
| $\alpha$  | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 10.0| 10.0| 10.0| 10.0| 10.0| 10.0| 10.0| 10.0| 0.1 | 0.1 | 0.1 | 0.1 |
| $\gamma$  | 1.0 | 1.0 | 1.0 | 10.0| 10.0| 0.5 | 0.5 | 1.0 | 1.0 | 10.0| 10.0| 0.5 | 0.5 | 1.0 | 1.0 | 10.0| 10.0| 0.5 | 0.5 |
### Table D.2 Benchmarks for TNO and BGC data and simulations with 19 sets of habit parameters

<table>
<thead>
<tr>
<th>switches</th>
<th>% route 1</th>
<th>% habit</th>
<th>costs</th>
<th>excess travel time</th>
</tr>
</thead>
<tbody>
<tr>
<td>TNO</td>
<td>BGC</td>
<td>TNO</td>
<td>BGC</td>
<td>TNO</td>
</tr>
<tr>
<td>EXP</td>
<td>25.9</td>
<td>10.1</td>
<td>77.8</td>
<td>85.9</td>
</tr>
<tr>
<td>set 1</td>
<td>25.3</td>
<td>5.0</td>
<td>65.2</td>
<td>86.7</td>
</tr>
<tr>
<td>set 2</td>
<td>20.5</td>
<td>2.6</td>
<td>60.3</td>
<td>78.3</td>
</tr>
<tr>
<td>set 3</td>
<td>25.4</td>
<td>3.5</td>
<td>68.3</td>
<td>90.7</td>
</tr>
<tr>
<td>set 4</td>
<td>19.9</td>
<td>8.3</td>
<td>49.9</td>
<td>63.7</td>
</tr>
<tr>
<td>set 5</td>
<td>26.9</td>
<td>9.2</td>
<td>63.6</td>
<td>85.9</td>
</tr>
<tr>
<td>set 6</td>
<td>20.7</td>
<td>1.7</td>
<td>62.4</td>
<td>80.6</td>
</tr>
<tr>
<td>set 7</td>
<td>25.0</td>
<td>3.0</td>
<td>69.9</td>
<td>90.9</td>
</tr>
<tr>
<td>set 8</td>
<td>20.3</td>
<td>2.6</td>
<td>60.8</td>
<td>76.6</td>
</tr>
<tr>
<td>set 9</td>
<td>25.0</td>
<td>3.6</td>
<td>68.4</td>
<td>90.5</td>
</tr>
<tr>
<td>set 10</td>
<td>19.3</td>
<td>7.5</td>
<td>49.3</td>
<td>61.5</td>
</tr>
<tr>
<td>set 11</td>
<td>26.5</td>
<td>9.0</td>
<td>63.7</td>
<td>86.0</td>
</tr>
<tr>
<td>set 12</td>
<td>20.6</td>
<td>1.6</td>
<td>62.7</td>
<td>79.1</td>
</tr>
<tr>
<td>set 13</td>
<td>24.7</td>
<td>2.9</td>
<td>70.1</td>
<td>90.9</td>
</tr>
<tr>
<td>set 14</td>
<td>24.0</td>
<td>2.7</td>
<td>69.3</td>
<td>91.1</td>
</tr>
<tr>
<td>set 15</td>
<td>26.3</td>
<td>4.1</td>
<td>70.8</td>
<td>91.4</td>
</tr>
<tr>
<td>set 16</td>
<td>26.1</td>
<td>10.7</td>
<td>60.7</td>
<td>80.0</td>
</tr>
<tr>
<td>set 17</td>
<td>27.3</td>
<td>8.3</td>
<td>68.0</td>
<td>87.3</td>
</tr>
<tr>
<td>set 18</td>
<td>23.8</td>
<td>2.3</td>
<td>70.1</td>
<td>91.2</td>
</tr>
<tr>
<td>set 19</td>
<td>26.2</td>
<td>3.6</td>
<td>71.3</td>
<td>92.0</td>
</tr>
</tbody>
</table>
Sensitivity Tests
Sensitivity Tests

Hmax=0.5, alpha=0.5, gamma=0.5
n=0.97, MSE=0.06

Hmax=0.8, alpha=0.3, gamma=1.0
n=0.95, MSE=0.05

Hmax=0.5, alpha=0.1, gamma=1.0
n=0.96, MSE=0.06

Hmax=0.8, alpha=0.1, gamma=0.9
n=0.96, MSE=0.06

Hmax=0.6, alpha=0.5, gamma=1.0
n=0.96, MSE=0.06

Hmax=0.8, alpha=0.5, gamma=0.9
n=0.96, MSE=0.06

Hmax=0.6, alpha=0.5, gamma=1.0
n=0.96, MSE=0.06

Hmax=0.8, alpha=0.5, gamma=0.9
n=0.96, MSE=0.06

Hmax=0.6, alpha=0.5, gamma=1.0
n=0.96, MSE=0.06

Hmax=0.8, alpha=0.5, gamma=0.9
n=0.96, MSE=0.06
Samenvatting

Automobilisten zijn vaak langer onderweg, en rijden meer kilometers dan ze zouden willen. Zelfs als we aanvaarden dat we de auto gebruiken om ons te verplaatsen is er sprake van inefficiënt gebruik van de aanwezige infrastructuur. Deze inefficiëntie leidt ertoe dat het autoverkeer meer congestie ervaart en meer voor het milieu schadelijke stoffen uitstoot dan noodzakelijk is. Een van de oorzaken hiervan kan zijn dat automobilisten onvoldoende geïnformeerd zijn over de beschikbare route-alternatiefen en de kenmerken (bijvoorbeeld de reistijd) daarvan. Gezien de schadelijke effecten van (de extra) automobiliteit is het van belang om de door onvoldoende informatie veroorzaakte, ongewilde automobiliteit te beperken.

Gedurende de laatste jaren worden in Europa, de Verenigde Staten en Japan grootschalige programma's uitgevoerd waarbinnen nieuwe verkeersinformatietechnologieën worden ontwikkeld en getest. De kosten van deze nieuwe technologieën zijn vaak hoog en de effecten ervan zijn niet van te voren bekend. Het doel van dit proefschrift is een methodology te ontwikkelen waarmee de effecten van nieuwe soorten informatie-technologie ten behoeve van de routekeuze en vertrekstijdekeuze van automobilisten kunnen worden ingeschat en voorspeld. Zo'n methodology bestaat op dit moment niet en is vooral van belang voor verkeersautoriteiten en beleidmakers die ermee een afweging zullen kunnen maken tussen de kosten en baten van verschillende, nieuwe informatiesystemen.

De methode om het doel te bereiken kan als volgt worden samengevat. Het probleem wordt eerst duidelijk afgelopen. Daarna wordt op basis van de bestaande literatuur over de betreffende informatietechnologieën, over de huidige technieken om verkeersgedrag te modelleren, en op basis van de psychologische literatuur over beslisgedrag, vastgesteld wat bruikbaar is om het probleem op te lossen. Voor zover er lacunes in de huidige technieken en theorieën bestaan, worden gedrags- en modelmatige assumpties geformuleerd. Uit het gevondene en nieuw geformuleerde wordt vervolgens een model gespecificeerd. Daarna
wordt op grond van empirisch onderzoek nagegaan in hoeverre het geformuleerde model beantwoordt aan de doelstelling.

Het proefschrift is als volgt opgebouwd: de eerste vier hoofdstukken van zijn voorbereidend van aard. Na de inleiding volgen hoofdstukken over informatie voor automobilisten (hoofdstuk 2), over huidige, relevante technieken om verkeersstromen te modelleren (hoofdstuk 3), en over dynamisch beslisgedrag (hoofdstuk 4). Het vijfde hoofdstuk is een overgangs hoofdstuk. Het vat de bevindingen van de eerste vier hoofdstukken samen en presenteert de gedrags- en modelmatige assumpties die de basis vormen voor het beoogde model. In hoofdstuk 6 wordt het uiteindelijke model gepresenteerd. In de hoofdstukken 7 en 8 wordt het empirisch onderzoek beschreven waar mee het model wat betreft routekeuze en de gevolgen van verschillende soorten verkeersinformatie hierop is getest, en waar mee de validiteit van het routekeuze-gedeelte van het model wordt vastgesteld. Hoofdstuk 9 tenslotte bevat de voornaamste conclusies en implicaties van het onderzoek.

De achtergrond voor het voor dit proefschrift uitgevoerde werk is het Europese DRIVE I project EUROTOPP dat van 1989-1992 werd uitgevoerd. Voor dat project werd door de auteurs, als onderdeel van een veel omvangrijker model, een eerste versie van het in dit proefschrift gepresenteerde model ontwikkeld. Dit model werd in dat kader ook gedeeltelijk getest. De inhoud van het proefschrift kan als volgt worden samengevat:

In het eerste hoofdstuk wordt de achtergrond van het werk voor dit proefschrift geschetst. De doelstelling wordt geformuleerd en de gekozen aanpak wordt verduidelijkt. Daarbij wordt het te beschouwen gedrag afgebakend: het gaat om routekeuze en vertrekstijdkeuze. De informatiesystemen die worden beschouwd bieden de individuele automobilist informatie om deze route- of vertrekstijdkeuze. Er wordt voorlopig vastgesteld dat het onder meer daarom noodzakelijk is om individueel keuzegedrag in beschouwing te nemen.

In hoofdstuk 2 wordt verkeersinformatie eerst algemeen besproken en vervolgens wordt een overzicht gegeven van een aantal relevante informatiesystemen die de routekeuze en vertrekstijdkeuze van automobilisten kunnen beïnvloeden. In de algemene bespreking wordt uitgegaan van de drie elementen die bij het verstrekken van verkeersinformatie van belang zijn: de informatie zelf, het verkeerssysteem en de verkeersdeelnemers. Er worden een aantal essentiële verschillen tussen verschillende soorten informatie aangegeven. Een belangrijk onderscheid is het verschil tussen beschrijvende en voorschrijvende informatie. Beschrijvende informatie is bijvoorbeeld een filemelding. Voorschrijvende informatie zegt bijvoorbeeld tegen de automobilist dat hij een bepaalde route moet nemen om zijn bestemming te bereiken. Verondersteld wordt dat mate waarin automobilistenzullen reageren op informatie, waarschijnlijk afhankelijk is van de geloofwaardigheid van de informatie voor de automobilist.
In hoofdstuk 3 wordt ingegaan op de huidige stand van zaken met betrekking tot verkeersmodellering. Er wordt een algemene indeling van verschillende, bestaande modeltechnieken gepresenteerd. Vastgesteld wordt dat deterministische, niet-stochastische modellen voor het huidige doel onbruiikbaar zijn omdat ze uitgaan van reeds perfect geïnformeerde reizigers. Statische modellen zijn onbruiikbaar omdat ze niet in staat zijn om rekening te houden met veranderingen in de tijd (dynamiek). Uit de beschrijving van de bestaande technieken wordt geconcludeerd dat alleen een beperkt deel van de stochastisch dynamische technieken toepasbaar is. Juist omdat als gevolg van informatievoorziening gedragsveranderingen in de tijd, c.q. van dag tot dag, optreden, is een eindoplossing die in evenwichtsmodellen wordt geformuleerd niet relevant. Het beste aanknopingspunt van de huidige modeltechnieken is microsimulatie waarmee individueel gedrag van dag tot dag kan worden bekeken (Mahmassani & Herman, 1984).

In hoofdstuk 4 wordt het keuzegedrag waarop het onderzoek zich richt vanuit de gedragswetenschappen benaderd. Gesteld wordt dat het betreffende keuzegedrag te beschrijven is als dynamisch beslisgedrag. Daarin worden beslissingen opeenvolgend in de tijd genomen, waarbij de taakomstandigheden in de tijd kunnen veranderen en de beschikbare informatie afhankelijk kan zijn van voorgaand gedrag, en kunnen beslissingen toekomstig gedrag beïnvloeden (Rapoport, 1975). Dynamisch keuzegedrag impliceert dat mensen verwachtingen opbouwen uit ervaring, met andere woorden, dat ze leren van wat ze meemaken. Het geleerde kan echter onvoldoende zijn om optimale beslissingen te kunnen nemen. Het geleerde bevat dus onzekerheid. Informatie kan ertoe leiden dat deze onzekerheid wordt verminderd of dat onjuiste verwachtingen worden gecorrigeerd. Ook kan informatie onwetendheid wegnemen, bijvoorbeeld door een voor de automobilist onbekende route aan te dragen. De mate waarin informatie van belang is voor een automobilist is afhankelijk van zijn behoefte aan informatie en zijn kennis. Er wordt vastgesteld dat gewoonte een belangrijke gedragscomponent in keuzegedrag kan zijn.

In hoofdstuk 5 wordt een brug geslagen tussen de voorgaande hoofdstukken die het kader voor het ontwikkelde model scheppen, en de daadwerkelijke formulering van het model die in hoofdstuk 6 plaatsvindt. Het hoofdstuk geeft een opsummating van de relevante assumpties die ten grondslag liggen aan de modelformulering.

In hoofdstuk 6 wordt het model gespecificeerd. Het hoofdstuk bestaat uit twee delen. In het eerste wordt een algemene, niet-wiskundige beschrijving van het model gegeven. Het tweede deel bevat een gedetailleerde, wiskundige formulering van het model. In hoofdlijnen bestaat het model uit de volgende componenten. Er kunnen drie beslisregels van toepassing zijn als automobilisten keuzes maken, namelijk maximalisatie van verwacht nut, gewoontegedrag en opvolgedrag. De eerste twee beslisregels kunnen in alle situaties van toepassing zijn, de derde kan alleen gelden als voorschrijvende informatie aan de automobilist
wordt verstrekt. Het model is dynamisch. Dit wil zeggen dat het keuzegedrag van dag tot dag wordt beschreven. Als een keuze is uitgevoerd wordt het verwachte nut steeds aangepast aan de opgedane ervaring. Gewoontegedrag is vooral afhankelijk van de keuze zelf, en in mindere mate van de ervaring. Het gebruik van informatie wordt afhankelijk verondersteld van de geloofwaardigheid van het informatiesysteem. Aan de hand van ervaring wordt de geloofwaardigheid steeds aangepast.

In hoofdstuk 7 wordt het routekeuze-gedeelte uit het model getest en gevalideerd voor een situatie waarin beschrijvende verkeersinformatie aan automobilisten wordt verstrekt. Het gaat hier om de keuzesituatie van automobilisten die via de A8 de ringweg A10 van Amsterdam naderen. Deze automobilisten krijgen even voordat zij de keuze moeten maken tussen de ring A10-West (Coentunnel) en de ring A10-Noord (Zeeburgertunnel) via een paneel van het RIA (Route Informatie Amsterdam) systeem informatie over de lengte van eventuele files voor de beide tunnels. Gegevens over het routekeuzegedrag in deze situatie werden verzameld bij een panel van automobilisten die frequent van de ringweg gebruik maken. Zowel voor de situatie waarin nog geen informatie werd gegeven als die waarin wel informatie werd gegeven, werden gegevens verzameld. Om de belangrijkste parameters van het model simultaan te kunnen schatten werd een schattingprocedure op basis van maximale aannemelijkheid ontwikkeld en vervolgens op de gegevens toegepast.

De validatie toont aan dat het model individueel (en dus ook aggregaat) routekeuzegedrag voor de onderzochte situaties goed kan beschrijven. Gedurende alle onderzochte tijdspijlers blijkt het keuzegedrag in sterke mate door gewoonte te worden bepaald. De positieve effecten van de informatie op het keuzegedrag worden duidelijk aangetoond.


Ook uit deze experimenten blijkt dat gewoontegedrag een duidelijk rol speelt in de keuzes die worden gemaakt. Het sterkste gewoontegedrag trad op in het experiment met voorschrijvende informatie. Taakverschillen tussen beide experimenten kunnen hiervan een oorzaak zijn.
In hoofdstuk 9 worden de conclusies van dit proefschrift uiteengezet en worden de verrichte onderzoeken bediscussieerd. De hoofdconclusies zijn dat de beoogde methodologie is ontwikkeld en dat het routekeuze-gedeelte van het model op grond van een tweetal empirische onderzoeken is gevalideerd, voor zowel situaties zonder informatie als voor situaties waarin beschrijvende of voorschrijvende informatie wordt gegeven. Omdat we niet de beschikking hadden over voldoende gegevens over vertrektijdkeuze (en ook geen gegevens over een situatie waarbij vertrektijdkeuze-informatie werd gegeven) kon het vertrektijdkeuze-gedeelte uit het model niet worden gevalideerd.

De bevindingen uit de validatiestudies hebben belangrijke consequenties voor de effecten van informatieverstrekking en verkeersmodellering in het algemeen. Ten eerste blijkt dat informatie steeds positieve effecten heeft op het routekeuzegedrag van automobilisten. De vrees dat een onbetrouwbaar informatiesysteem er onmiddellijk toe leidt dat automobilisten het systeem de rug toe keren, is niet gerechtvaardigd. Weliswaar reageren automobilisten op onjuiste informatie door deze minder op te volgen, maar zolang het systeem enige betrouwbaarheid heeft, zullen automobilisten van de informatie gebruik maken. Goede ervaringen met het systeem compenseren slechte, voorgaande ervaringen, en het opvolggedrag herstelt zich snel.

Bovendien blijkt dat informatie er toe leidt dat automobilisten betere verwachtingen opbouwen en beter keuzegedrag vertonen. Dit betekent dat het toepassen van nieuwe verkeersinformatietechnologie een waardevol verkeersmanagement instrument is.

Curricula Vitae
