Decision Field Theoretical Analysis and Modelling of Dynamic Route Choice Deliberation Process

by

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ABSTRACT

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Intelligent Transportation Systems applications require a thorough understanding of drivers' route choice behaviour in a complex network under real-time information. This research attempts to describe and model route choice behaviour at the disaggregate individual level and from a psychological decision-making process perspective. We base our proposed behavioural route choice theory and model of the drivers' mental deliberation process on the scientifically-sound Decision Field Theory (DFT). DFT is a process-oriented modelling ground of individuals' decision making that simulates the evolution of preferences during deliberation.

Laboratory experiments are conducted that expose human subjects to realistic network and traffic conditions while monitoring and recording their route choices under varying experimental conditions. Recorded data are used for analyzing drivers' route choices and for the development and calibration of a DFT-based route choice theory and framework. A simple "mixed reality" simulator is developed to serve as an experimentation platform. The mixed reality platform enables a driver to use a PC-based steering device to navigate through a microscopic simulation model of the waterfront portion of downtown Toronto. Analysis results reveal the significance of the impacts of

some situational factors (e.g. information content, information reliability, and inertia effects), and some personal factors (e.g. gender differences), on drivers' route choice attitudes.

Estimation of the DFT route choice model parameters is performed based on the experimental observations. Genetic algorithms are used as the optimization tool to calibrate model parameters and minimize the discrepancy between model output and observed behaviour. The developed DFT model is used to study the impact of time pressure constraints on drivers' compliance behaviour. Variations in impact trends are estimated with varying information characteristics (form and reliability).

Finally, an alternative structural-oriented parameter estimation methodology is adopted for comparative purposes. In the structural-oriented methodology, the deliberation time dimension is completely ignored during the estimation of the model parameters. Analysis results reveal the superiority of the process-oriented DFT route choice model in improving the credibility of route choice predictions. Furthermore, the developed DFT model contributes to enhancing the understanding of the impact and the influence mechanisms of personal/situational factors on drivers' route choice attitudes.

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GLOSSARY OF ABBREVIATIONS

ANN	Artificial Neural Networks
ANOVA	Analysis of Variances
API	Application Programming Interface
ASP	Anticipated State Probability
ATIS	Advanced Traveller Information Systems
BDT	Behavioural Decision Theory
C	Compliance recommendation attribute
COM	Component Object Model
CV	Coefficient of Variation
D	Distance attribute
DFT	Decision Field Theory
DHH	Descriptive information scenario High congestion level on the Gardiner High congestion level on Lakeshore
DHL	Descriptive information scenario High congestion level on the Gardiner Low congestion level on Lakeshore
DHM	Descriptive information scenario High congestion level on the Gardiner Medium congestion level on Lakeshore
DT	Deliberation Time
DTA	Dynamic Traffic Assignment
EA	Evolutionary Algorithms
EBA	Elimination by Aspect
ED-model	En-route Descriptive-Information Deliberation model
EP-model	En-route Prescriptive- Information Deliberation model
F	Freeway usage attribute
G	Gardiner
GA	Genetic Algorithms

H	High congestion level
IC	Input Capturing
IPC	Inter-Process Communicator
ITS	Intelligent Transportation System
L	Low congestion level
LA	Learning Automata
LS	LakeShore
M	Medium congestion Level
MAPE	Mean Absolute Percent Error
MDT	Mean Deliberation Time
MET	Microeconomic Theory
MNL	Multinomial Logit
NK	New Knowledge
No-info	No information scenario
OD	Origin-Destination
OK	Old knowledge
PG	Prescriptive information scenario "Take the Gardiner"
PLS	Prescriptive information scenario "Take Lakeshore"
PN-model	Pre-trip No Information Deliberation model
RL	Reinforcement Learning
SEU	Subjective Expected Utility
TT	Travel Time
VMS	Variable Message Sign
%G	Gardiner-choice percentage

1 INTRODUCTION

Prolonged daily periods of traffic congestion waste time and money and degrade both the environment and our quality of life. Transportation planners attempt to meet increasing travel demands through a hierarchy of strategies: (1) supply management, (2) demand management, and (3) land-use management. Common supply management strategies were traditionally focussed on the expansion of the transportation network capacity, such as, for instance, building new highways. Capacity expansion, however, failed to keep pace with sharp increases in demand, resulting in widely spreading congestion and raising concerns about the long-term sustainability of this approach. Over the past two decades, focus has dramatically shifted from myopic capacity expansion to more sustainable alternatives, such as demand and land use management and the use of technology to improve real-time supply management. Increased congestion and pollution, coupled with fiscal and space constraints, are empowering this paradigm shift in dealing with transportation problems. The focus on using modern technologies in transportation management gave rise to Intelligent Transportation Systems (ITS). ITS are concerned with the application of emerging information technology to transportation systems in order to improve their efficiency, reliability, and safety. As information technologies and advances in communications continue to revolutionize all aspects of our lives, real-time control of our transportation network becomes more viable. The implementation of such advanced systems is steadily becoming a reality that will reshape the way people, vehicles, and technology interact.

Intelligent Transportation System applications require a thorough understanding of drivers' route choice behaviour in a complex network, and possibly under real-time information. Dynamic traffic assignment, dynamic route guidance, flow prediction, and adaptive traffic control are but a few examples of such applications. Both the aggregate route choice behaviour of the population (e.g. user equilibrium) or disaggregate behaviour (e.g. how an individual driver perceives and reacts to real-time information) are of interest. The success of ITS applications depends on the accuracy and reliability of network condition assessment, prediction, information dissemination, and control formulation, possibly in real time. The predictive accuracy of disseminated information and formulated control strategies require realistic understanding and representation of drivers' route choices, which motivates the current research.

1.1 Problem Statement

At the disaggregate level, drivers' route choices are inspired by a number of interrelated psychological/cognitive processes. Our focus is on the mental deliberation process that leads to the selection of a travel route. The deliberation process refers to a psychological process whereby drivers trade-off between attributes of the choice alternatives under prevailing personal/situational conditions and constraints. This process is often complicated by uncertainty and limited time before a choice has to be made. In the route choice literature, modelling of the deliberation process is usually addressed from two perspectives: microeconomics and behavioural perspectives. The microeconomic perspective adopts utility-based choice models to represent the trade-off between the choice situation attributes. The utility-maximization principle has, historically, been the conventional decision rule of most route choice modelling frameworks. This is in spite of the fact that it has been repeatedly questioned as a realistic basis for travel-choice modelling. This is mainly due to its underlying normative assumptions regarding decision-makers' rationality, perfect knowledge, and infinite processing capabilities (Algers, 1998; Stern, 1998). Alternatively, the behavioural perspective realizes the need for modelling the psychological process of mental deliberation preceding a choice selection. This modelling approach attempts to closely mimic the actual mental deliberation process, thereby potentially enhancing the realism and the credibility of drivers' route choice models.

The behavioural perspective of route choice has been the focus of several research studies throughout the past decade. However, there remains a lack of a realistic explanatory representation of the psychological *process* underlying drivers' choice decisions. The structural-oriented modelling approach of the deliberation process has been the focus of most existing modelling frameworks. The structural approach attempts to formulate a relationship between inputs (choice situation attributes) and outputs (choices), paying little attention to understanding/modelling the underlying psychological process. The generalization of this type of model is questionable, as it might result in severe mis-predictions (Stern, 1998). Drivers' choices are performed within a challenging choice environment characterized by uncertainties and time pressure constraints. The dynamic nature of the choice environment entails a shift of focus from the structural-oriented modelling approach to a process-oriented one. From a process-oriented modelling perspective, choices are direct outputs of a psychological process. Prediction of a process output entails the theoretical abstraction of the process itself: understanding how decisions are made and how they evolve with time. As such, there is a need to develop a scientifically sound behavioural route choice theory that could explain the cognitive mechanisms of deliberation during the route choice process. It's noteworthy that the need for this detailed level of modelling is recognized within traffic operations and short-term transportation planning activities.

1.2 MOTIVATION

On one hand, drivers' route choice decisions are the outcome of complex deliberation processes involving uncertainty. Uncertainty is a typical characteristic of any traffic network, even under real-time congestion information. There is uncertainty on the demand side as well as the supply side of the network. Moreover, there is another dimension of uncertainty within traffic information sources. The reliability of disseminated information is never guaranteed.

On the other hand, choice decisions are not instantaneous but rather time-consuming (Busemeyer and Townsend, 1993). The direct influence of the length of a deliberation process on choice decisions cannot be ignored. Drivers are commonly faced with divergence decisions while driving. The length of the deliberation process is restricted to a time frame prior to tentative bifurcation or divergence points. Available time frames might vary according to many factors, such as driver familiarity with the network geometry, daily traffic conditions, and the timing and location of information dissemination. Limited deliberation time frames pressure drivers to make choices possibly before their preferences mature to a satisfactory level.

In formulating our behavioural perspective of the dynamic route deliberation process, this research has been inspired and influenced by recent advances from the field of psychology. Of particular interest to us is the *time-dependent psychological and* *mental process of preference formation in an uncertain and time-pressed choice environment.* Of direct relevance to our perspective in this research is the sound and well established Decision Field Theory (DFT), which forms the theoretical basis for modelling the psychological process underlying drivers' route choice decisions. DFT, developed by Busemeyer and Townsend (1993), is a dynamic behavioural theory that is able to capture the psychological process involved in general choice decisions under uncertain conditions. DFT is one of a few process-oriented behavioural decision theories that explicitly accounts for varying degrees of uncertainty as well as time pressure in a unified, scientifically sound framework.

1.3 OBJECTIVES

This research aims to establish a process-oriented modelling approach for the deliberation process underlying drivers' route choices. The modelling framework is founded on the basis of DFT abstraction of decision-making. A DFT route choice model is the general objective of this research. The following is a list of the more specific research objectives:

1. **Design a DFT Route Choice Model Conceptual Framework**
   a. Develop a base-case modelling framework for drivers' pre-trip and en-route deliberation processes based on the foundation of DFT (with no information provision). This entails the definition of: (1) process schematic, (2) decision variables, and (3) decision parameters.
   b. Develop an integration framework for information provision within the base-case modelling framework. The provision of traveller information and route guidance is central to ITS and requires an accurate representation of drivers' choices. Therefore, the representation of information provision within our DFT modelling framework is necessary.
2. **Develop an Operational DFT Route Choice Model**
   a. Develop a low-cost "mixed reality" infrastructure that serves as an experimental platform for capturing the route choice behaviour of test subjects in a controlled lab setting. In the mixed reality environment, a human subject is allowed to "route" a vehicle in a microscopic traffic

simulation model of an actual physical network. The virtual reproduction of the choice environment increases the realism of the simulated driving experience and route choice behaviour.

b. Experimentally observe, capture, and analyze test subjects' route choice behavioural patterns. One approach to such analysis is to conduct a set of in-lab simulated driving experiments using human subjects in the mixed reality environment for the purpose of data collection. The experimental data enable the investigation of the impact of different personal/situational factors on drivers' route choice attitudes.

c. Estimate the DFT route choice model parameters based on the experimental results. Parameter estimation requires the development of an optimization approach to solve for the model parameters that minimize the discrepancy between the model output and actual observed behaviour.

3. **Analysis and Benchmarking**

   a. Use the DFT model to analyze the dynamics of deliberation by studying the effect of time pressure constraints on route choices. This analysis uses the DFT model to generate simulated route choice scenarios under varying time constraints.

   b. Benchmark the performance of the developed process-oriented DFT route choice model against the more traditional structural-oriented parameter estimation approach.

1.4 Scope

The following section briefly outlines the research scope along a number of dimensions. Specific details are discussed in respective chapters.

1.4.1 Conceptual Framework

DFT is adopted as a theoretical foundation for modelling drivers' pre-trip and en-route deliberation processes. Deliberation is a trade-off between perceived attributes of the choice alternatives. Choice alternatives are outputs of a choice set formulation process. Modelling of the choice set formulation process is beyond the scope of this research and hence, is not addressed in our modelling framework. Choice alternatives are treated as external inputs to our route choice model.

In real life, drivers' perceptions of the choice alternative attributes are continuously updated based on day-to-day experiences, day-specific experiences, and available current information sources. A complex learning process underlies the cumulative long-term experience with alternatives. Current observation of the surrounding environment and available information about the rest of the system are amalgamated with the learnt perception to influence the decision process. While information-based updates (descriptive and prescriptive information) are explicitly addressed in our modelling framework, learning-based updates are limited. Detailed modelling of this learning process, although intriguing and important, is outside our research scope. In this research, we only expose each of the subjects of our experiments to a relatively short 'learning' session before they embark on the actual experiments. The purposes of the learning session are: (1) to allow the subjects to first familiarize themselves with the experimental setup, and (2) for the subjects to 'learn' about the network, its geometrical and traffic conditions, and the reliability of the provided information. As such, drivers' experience-based perception updates are assumed to have reached a steady state where they perceive the average statistics of travel patterns and information reliability.

In summary, the scope of our DFT route choice model conceptual framework is restricted to modelling drivers' deliberation processes in two choice contexts (pre-trip, and en-route) and under three information-related scenarios (no information, descriptive information, and prescriptive information). No attempts have been made to elaborately model drivers' learning processes or choice-set formation processes. Moreover, drivers are assumed to want, seek, and use traveller information when available. If they opt not to, their behaviour is assumed to be covered under the case of no information.

1.4.2 Mixed Reality Experimental Platform

A low-cost mixed reality experimental platform is developed by integrating a microscopic traffic simulator with a driving simulator. In such a mixed reality environment, actual human subjects can experience a driving experiment while the surrounding roads, traffic levels, and congestion evolution are modelled and controlled using a microscopic simulator in a full-scale network model. The objective is to enhance the realism and credibility of in-lab simulated route choice experiments under various ITS applications. This is achieved by integrating an externally controlled driving capability into the widely used Paramics microscopic traffic simulator. The scope of this work is limited to vehicle routing control (lane changes and turning at bifurcations). No attempt has been made yet to control longitudinal driving tasks such as acceleration and braking, which are left to the car-following model of the microscopic simulation model.

1.4.3 Laboratory Experiments

In-lab simulated route choice experiments are conducted for route choice data collection. A set of experiments is designed for this purpose. A limited sample size of 30 subjects is used due to the difficulty of obtaining volunteer test subjects and the length of time required for each subject to repeat the experiments hundreds of times, which is the nature of such experiments. The sample of drivers is homogenous in terms of age group, education level, and driving experience. Experimentation is focused on recurrent-type trips (e.g. work or school trips). Variable message signs communication technology is used as the tool for information dissemination. Only two types of information forms are considered: descriptive (level of congestion) and prescriptive (route recommendation) forms.

1.4.4 Operational Model

An operational version of the DFT route choice model is realized by estimating model decision parameters using the experimental observations. The adopted parameter estimation methodology is based on the use of aggregate observations (i.e. estimate the optimal model parameters that reproduce the aggregate observed behaviour of the sample). Observed data are categorized into a number of homogenous groups. Aggregate observations from each group are used to estimate group-specific parameters. Given the limited sample size, estimated parameter values are considered prototypical values for each class of drivers. As such, the developed operational model is only a limited-scale prototype of the envisioned one. Further wider-scope experimentation is required to enable the development of a generic, full-fledged DFT route choice model.

1.5 THESIS ORGANIZATION

This thesis is organized into 9 chapters. Chapter 2 summarizes the review of the literature on the route choice modelling problem. The problem is abstracted into a number of interrelated processes. Each of the abstracted processes is discussed, in relevance to the main modelling streams of route choice literature. Based on a thorough review of relevant literature, a synthesis of the major route selection contributing factors is presented. Chapter 3 presents the conceptual DFT framework of the route choice process. A base-case framework, with "no information" provision, is first discussed. An integration framework, for descriptive and prescriptive traffic information is then proposed.

Chapters 4 and 5 are concerned with laboratory experimentation. Chapter 4 presents the development details of the mixed reality experimental platform. The details of the design of experiments are discussed in Chapter 5. Assessment of drivers' route choice patterns, based on experimental observations, is undertaken in Chapter 6. Chapter 7 describes the estimation of the route choice model parameters. An investigation of the impact of the deliberation-time dimension on drivers' route choice modelling is the focus of Chapter 8. In this chapter, the added value of adopting a process-oriented modelling framework is benchmarked. Finally, Chapter 9 summarizes the conclusions of this research and proposes directions for future work.

2 BACKGROUND AND LITERATURE REVIEW

2.1 Précis

Drivers' route choice behaviour evolves from several interrelating cognitive processes. The simultaneous interaction of these processes within the available time constraints influences and ultimately gives rise to drivers' choice decisions. Understanding and modelling drivers' route choices entails the explanation of the underlying psychological processes. Four main processes are abstracted in this context: (1) decision-making, (2) learning, (3) information acquisition, and (4) experience/information integration processes. An overview of the relevant previous modelling efforts in light of these processes is presented in this chapter. Being the subject of this research, an increased focus is devoted to the decision-making process in terms of modelling approaches and perspectives. Based on this review, a vision of modelling needs is synthesized.

On the other hand, drivers' route choice behaviour is influenced by many internal/external factors. Modelling of drivers' decision-making processes mandates a fair knowledge of the main contributing factors. As such, based on a thorough review of relevant literature, a synthesis of the main contributing factors is discussed.

2.2 Overview of Route Choice Behaviour

Drivers' route choices are outcomes of complex interactions of several psychological processes. Drivers make their choices through a mental deliberation process that includes a trade-off between the perceived attributes of available alternatives. Drivers form perceptions about these attributes based on previous experiences, day-specific experiences, and, in many cases, traffic information sources. Driver characteristics (such as socioeconomic/demographic characteristics and risk attitude), and trip-specific characteristics (such as trip purpose and arrival time constraints) influence the operation of the underlying psychological processes and the resulting choices. On the other hand, drivers' route choices are performed within a unique choice environment. The complexity of the choice environment stems from several contributing factors, the most prominent of which are uncertainty and time pressure. In addition, situational conditions (such as incidents and delays), and environmental conditions (such as weather-related obstructions) further impact drivers' perceptions of the decision attributes. The highly intertwined aspects of the overall route choice behaviour mandate the abstraction of the main underlying processes/factors for understanding and modelling purposes. Figure 2.1 illustrates an abstract representation of the main contributing processes/factors and their interrelations.

During the past decade, understanding and modelling of route choice behaviour have been the focus of numerous research efforts. In the following sections the main research streams are discussed, in relevance to the abstracted processes. Nonetheless, being the focus of this research, a more vigorous discussion is devoted to the deliberation part of the decision-making process. A synthesis of the main contributing factors to the operation of all discussed processes is then presented.

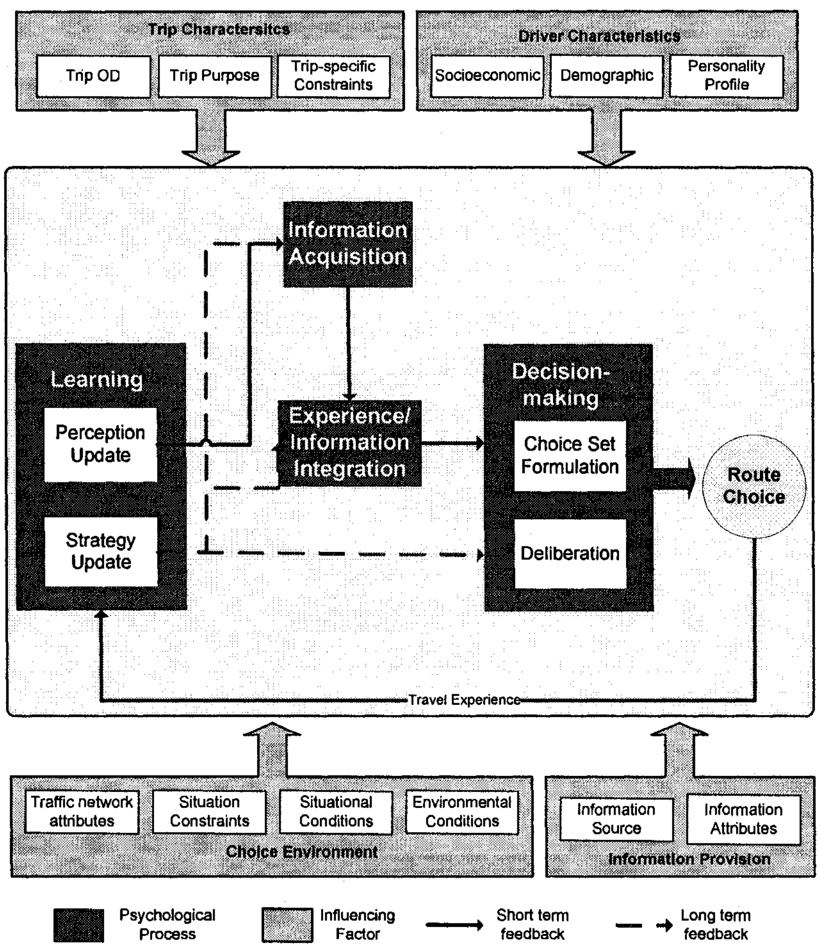


Figure 2.1 Route Choice Behaviour Abstraction

2.3 DECISION-MAKING PROCESS

The decision-making process refers to a mental process whereby individuals trade-off between perceived attributes of alternative courses of action. This process begins when an individual is confronted with a choice situation and ends when a final decision is reached. Deliberation is based on up-to-the-moment formulated perceptions of the different attributes/aspects of the choice situation. Modelling drivers' decision-making process embeds the challenging task of modelling human behaviour. The human being is portrayed by Algers (1998) as "an agent driven by psychological factors in a system of economic relations and restrictions in a spatial context." As such, many disciplines, such as economics, psychology, sociology, and engineering, attempt to model individuals' decision-making process from different perspectives.

The decision-making process could be further divided into two sub-processes: a choice-set formulation, and a deliberation process. Choice-set formulation constitutes the initial stage in the choice process wherein drivers establish their choice alternatives. The outcome of any decision-making process is a choice of a certain alternative among a number of available ones. Thus, appropriate specification of available alternatives is essential to any modelling approach. The available routes between a given Origin Destination (OD) pair are the natural alternatives of a route choice situation. However, feasible paths between any OD pair are numerous and probably not all are perceived by all drivers (Cascetta *et al.*, 2002). In addition, it is unrealistic to assume that drivers consider a large number of alternative routes simultaneously (Khattak *et al.*, 1995). As such, a behaviourally realistic choice-set formulation model is of prominent importance in modelling drivers' decision-making processes. In the literature, choice-set generation models are rarely explicitly specified and are calibrated based on indirect information (Cascetta *et al.*, 2002). Cascetta *et al.* (2002) presented a simplified taxonomy of the different approaches adopted in the literature for route choice-set generation. In the referenced study, a utility-based explicit choice-set generation model is proposed. Initial calibration results are also reported.

The second stage in the decision-making process is concerned with mental deliberation. The deliberation process involves the evaluation of different courses of action, generated in the initial step, based on formulated perceptions. Generally, this process is addressed in the literature from two perspectives: microeconomic theory and behavioural decision theory. An overview of these two perspectives is presented in the following sections.

2.3.1 Microeconomic Theory

Microeconomic Theory (MET) represents decision making as a rational evaluation of the economic consequences of different courses of action. An expected-utility function is adopted to quantify these consequences. Decision-makers are assumed to possess perfect knowledge of the choice situation. Decisions are made based on a utility-maximization principle. As such, choices are predicted based on an understanding of risk attitudes and budget restrictions (Garling *et al.*, 1998).

Random utility theory was then introduced to capture the differences between individual consumers through the incorporation of a random term. Most conventional route choice models fall under the category of random utility-based models (for example: Daganzo and Sheffi, 1982; Ben-Akiva *et al.*, 1984; Cascetta *et al.*, 1996; and Abdel-Aty and Abdalla, 2000). The utility of each alternative contains a systematic component corresponding to the choice attributes and a random-error term corresponding to unobserved attributes, taste variations, measurement errors, imperfect information, etc. It is assumed that each individual attempts to maximize her/his utility. A maximum-likelihood approach is typically used to estimate the coefficients of the various attributes.

There is a fairly large variety of random utility-based models with different assumptions regarding the correlation between random residuals (Cascetta, 2001). The simplest of these are the Multinomial Logit (MNL) models, assuming no correlation between residuals. In spite of this unrealistic assumption, MNL models are still used in some modelling frameworks due to their simplicity and ease of use. To overcome the simplified assumption of the MNL models, other utility-based models, such as Nested-Logit, Cross-Nested Logit, and Probit models, were proposed.

In the literature, MET has been repeatedly questioned as a basis for travel choice modelling. This is to a large extent because of its inability to model the choice process itself rather than formulating a relationship between input and output variables (Algers, 1998). The embedded normative assumptions (rationality, perfect knowledge, infinite processing capabilities), within the utility-based modelling framework, are behaviourally unrealistic. In addition, the adequacy of a single random term for encapsulating the different sources of ambiguity, randomness, and uncertainty is questionable (Stern, 1998).

In an attempt to incorporate behavioural components within MET, some extensions and modifications are proposed (Algers, 1998). One of the main modifications, adopted for modelling route choice decisions, is the bounded-rationality principle (Mahmassani *et al.*, 1986 and Mahmassani and Chang, 1987). Departing from the formal utility-maximization paradigm, the bounded-rationality principle implies that for a route switch to be made (in pre-trip route selection and en-route path switching), expected travel time savings have to exceed a threshold value (user-indifference band). This value is individual/situational specific. The transportation research group at Texas Austin, under the supervision of H. Mahmassani, adopted the bounded-rationality principle as a governing criterion in drivers' pre-trip and en-route choices in several studies (Hu and Mahmassani, 1997; Mahmassani and Liu, 1999; Mahmassani and Jou, 2000; and Srinivasan and Mahmassani, 2000). The bounded-rationality principle was also adopted as a behavioural component of drivers' route choice in the simulation-based Dynamic Traffic Assignment (DTA) software DYNASMARTX-DTA (Mahmassani, 2001).

Along the same line of research, Adler *et al.* (1993) adopted conflict assessment and resolution theories in their utility-based modelling of en-route choice behaviour. Drivers are assumed to be rational, trying to satisfy a set of goals. A utility function defines the degree of goal attainment for each alternative route. Responses are motivated by conflict arousal due to unexpected changes in the choice environment. An individual-specific degree to tolerate conflict, among other factors, stimulates responses.

2.3.2 Behavioural Decision Theory

Behavioural Decision Theory (BDT), drawn from psychology and behavioural science, is introduced as an alternative perspective for modelling drivers' choice decisions. BDT, as defined by Algers (1998), "refers to an empirical approach to the study of human decision making with the goal of describing and understanding how people actually make decisions." Similar to MET, BDT proposes that a good decision is one that satisfies the decision-maker's objectives. However, the question remains whether individuals make good decisions (Algers, 1998). To answer this question, a number of decision theories have emerged in an attempt to explain the choice mechanism from a behavioural perspective. Various modelling approaches have been adopted.

2.3.2.1 BDT Modelling Approaches

In the following brief overview, the different modelling approaches are classified along a set of orthogonal dimensions (Busmeyer and Townsend, 1993; Svenson, 1998; and Stern, 1998):

1. *Modelling Strategy*
   - **a. Structural Approach**: concerned with formulating a relationship between information about alternatives (decision inputs) and the choice between them (decision output) (Stern, 1998). This approach models the final decision while paying little attention to the cognitive process leading to that decision.
   - b. **Process Approach**: concerned with modelling the cognitive process underlying choice decisions. This approach attempts to explain how decisions are made and how they evolve over time (Stern, 1998).
   - c. **Prospect Approach**: concerned with a two-phase decision process: editing and evaluation phases. In the editing phase, possible decision outcomes are ordered based on some heuristic. A reference is set to distinguish between losses and gains. In the evaluation phase, a value is computed for every alternative, based on its potential outcome with respective to perceived probabilities of occurrences (Kahneman and Teverky, 1979). This approach ignores the time component and, hence, lies in between the structural and the process approaches (Stern, 1998).
2. *Incorporating Uncertainty*
   - **a. Risk-less Approach:** decision-makers are certain about the outcomes of their choices.
   - **b. Risky Approach:** there exist levels of uncertainty in perceived outcomes.

3. *Representation of Preference Relations*
    a. **Deterministic Approach:** output preference relations are either true or false for any alternative action (Busmeyer and Townsend, 1993).
    b. **Stochastic Approach:** output preference relations are represented by probability functions (Busmeyer and Townsend, 1993).
4. *Behavioural Assumptions*
    a. **Normative Approach:** specifies how decisions should be made with respect to rational behaviour.
    b. **Prescriptive Approach:** maintains the rationality assumption; however, it does consider the mechanisms in which individuals evaluate and integrate information (Stern, 1998).
    c. **Descriptive Approach:** attempts to abstract the psychological process underlying choice decisions with no prior assumptions.
5. *Time Factor Incorporation*
    a. **Static Approach:** assumes that decisions are made instantaneously, based on collective perceptions of different attributes/aspects of the choice situation. Thus, choices are independent of the deliberation time frame.
    b. **Sequential Approach:** assumes that final decisions are the last of a series of successive decisions, each changing the situation for the next decision (Stern, 1998). Such decisions are made sequentially in time.
    c. **Dynamic Approach:** this approach realizes the dynamic nature of the decision-makers' choice environment. During deliberation, the decision maker's preferences dynamically fluctuate with time. Choices depend on the level of preferences at the decision time. As such, this approach attempts to model the evolution in the decision-maker's preference relations over the deliberation time. Final decisions are, therefore, a direct output of the modelled evolution.

2.3.2.2 MET from a BDT Perspective

For a long time, modelling of the decision-making process has been viewed from the MET (utility-based) perspective. If we may map the utility-based modelling approach onto the BDT dimensions, it could be regarded as structural, riskless, deterministic, normative, and static modelling approach. Random utility-based models further capture the stochastic aspects of decision making. While MET have been strongly refuted as behavioural decision theories, they are still used in benchmarking many of the emerging BDTs, especially the structural-oriented ones (Svenson, 1998). In contrast to MET, this research is seeking a BDT-based route choice modelling approach that is process-based, risky, stochastic, descriptive, and dynamic, as will be discussed in the remainder of this dissertation.

2.3.2.3 Further Behavioural Improvements of Route Choice Models

Within the route choice modelling arena, numerous improvements of the behavioural credibility of route choice models have been proposed and researched. Different modelling methodologies have been adopted in this regard. These approaches, although varying in the underlying core methodology, all depart to varying extents from the traditional MET. They share a common target, which is to produce more behaviourally realistic route choice models. In the sections that follow, the main research streams are identified and summarized.

- *Rule-based Methodology*

A decision strategy is defined by Payne *et al.* (1993) as "a sequence of mental and effector (actions on the environment) operations used to transform the initial state of knowledge into a final goal state of knowledge." Decision-makers are realized to have limited processing capacities, and they attempt to make their decisions within some internal (such as effort) and external (such as time) constraints (Ben-Akiva *et al.*, 1991). As such, the rule-based modelling methodology assumes that drivers resort to heuristics (such as rules of thumb) to perform route choice decisions (Lotan and Koutsopoulos, 1993). The complexity of the process is, thus, a result of the simultaneous consideration of multiple simple rules rather than a single sophisticated one. The operations in the rule-based decision strategies are represented by a sequence of productions of the form "IF (condition 1...condition n), THEN (action 1...action m) (Payne *et al.*, 1993). The adopted rules are based on common sense and intuitive behaviour.

Based on these concepts, Lotan and Koutsopoulos (1993 and 1999) adopted an approximated reasoning framework to model drivers' route choice behaviour. Their modelling framework assumes that a driver's decision-making process could be represented by the logic of fuzzy perceptions and inference rules based on approximate reasoning. The core of the model is a set of if-then rules in which several rules contribute to the final decision. An if-then rule is composed of a condition part and an action part. The condition part deals with the driver's perceptions of the choice situation attributes. The action part is choice related. Both conditions and actions can include linguistic labels (such as; "if route x is very bad, I'll probably take route y"). The developed model can handle fuzzy data, incorporate linguistic rules, and facilitate flexible rule interpretations. Based on changing network conditions, rule consequences are adjusted through an approximate reasoning mechanism. All the adjusted rule consequences are then applied in parallel, resulting in a final attractiveness of each alternative. The final attractiveness of each of the alternatives is then compared and the most attractive alternative is chosen.

Nakayama and Kitamura (2000a) adopted a rule-based modelling framework of drivers' route choice decisions. Their model represents drivers' decision making as a production system in which a set of if-then rules is compiled. These rules are continuously revised by applying genetic algorithms operations. The condition portion of their if-then rules is composed of a set of binary bits. The condition implied by the bits is checked against the data in the memory to determine whether a certain rule would be activated or not. Finally, if more than one rule is activated, the one that has previously provided the best instructions is selected. This selection is based on an inferiority indicator, which is updated after each choice decision.

Peeta and Yu (2004) developed a hybrid probabilistic-possibilistic model of drivers' route choice behaviour. The use of the rule-based methodology, within this approach, is limited to producing quantitative values for qualitative-type variables. Qualitative variables are those with linguistic labels and subjective interpretations. Choice decisions are, however, based on a utility-based discrete choice model.

In addition to the above rule-based models, several other similar modelling efforts have been reported (for examples see Pang *et al.*, 1999). In general, the rule-based methodology, with its underlying fuzzy logic, addresses the uncertainty and vagueness in many traffic and transportation models (Teodorovic, 1994). As such, rule-based approaches could be classified as a risky, stochastic decision-making modelling approach. However, the lack of a cognitive explanatory mechanism of the decision-making process and the inability to account for the direct influence of the deliberation time dimension in choice decisions render these models to be undesirably structural, prescriptive, and static models.

- *Reinforcement Learning*

Drivers' route choice behaviour is viewed, by some researchers, from a strict learning perspective. Drivers are, therefore, assumed to update their choices, rather than their perceptions of the choice attributes, based on past experiences. A Reinforcement Learning (RL) methodology is proposed to model drivers' overall route choice behaviour. Learning could be defined as a change in behaviour as a result of past experience, and, hence, a learning system should have the ability to improve its behaviour with time (Abdulhai and Kattan, 2003). Within a RL framework, a driver is perceived as an agent whose goal is to make a certain trip from a specific origin to a specific destination with minimal travel time. The agent is expected to learn about its environment through repeated experiences, evaluating the consequences of daily choices and reinforcing the value of past good choice that are likely to maximize choice rewards.

Along the lines of a similar learning approach, Ozabay *et al.* (2001) proposed a stochastic Learning Automata (LA) framework to model driver's route choice behaviour. LA is considered a class of RL systems (Sutton and Barto, 1998). LA is concerned with unsupervised learning, where agents learn from their interaction with the environment. In their study, drivers' route choice probabilities are directly updated on the basis of received information and previous experiences. Ozbay *et al.* (2002) extended this model to account for the departure time choice dimension.

While drivers' route choice behaviour includes learning, the deliberation part cannot be neglected. The use of RL methodology in a stand-alone fashion would have the shortcoming of ignoring the deliberation side of the overall process. Choices are direct outcomes of a learning process. The resulting models are, therefore, structural-oriented. In addition, the reward maximization principle inherent to RL methodologies implies the rationality assumption in a prescriptive sense. A static characteristic of this modelling methodology, from the deliberation perspective, is also quite evident.

- *Artificial Neural Networks (ANN)*

ANN are simplified electronic models of the central nervous system. They are networks of highly interconnected computing elements that can respond to inputs and to learn from previous experiences. ANN are founded on the basis of learning, generalization, and abstraction to solve complex problems with non-algorithmic solutions (Tveter, 1998). ANN are primarily used for tasks including pattern recognition and classification and, hence, are mainly used for traffic pattern recognition within the traffic operations domain (Lyons and Hunt, 1993).

ANN were introduced as a modelling framework for traveller-related choice behaviour by Lyons and Hunt (1993). ANN are used to map attributes of alternatives to drivers' choices. However, this approach did not receive much attention, as it was perceived to be less representative of drivers' decision-making process than rule-based models (Stern *et al.*, 1998). ANN adopt an extremely structural-oriented modelling approach, as they mainly relate inputs and outputs through a black-box-type regressive relationship.

- *Prospect Theory*

Prospect Theory (Kahneman and Tversky, 1979) is one of the most recognized decision theories in contemporary behavioural-decision research (Svenson, 1998). The theory departs from the dominant utility-maximization principle to a more behaviourally realistic ground. In Prospect theory, decisions are made in two stages. First is an editing stage in which information is simplified and restructured. Second is an evaluation stage in which decision-makers consider the probabilities of different choice outcomes. Risk attitude is varied with respect to the choice frame. A concave value function is assumed for gains, while a convex, steeper, one is assumed for losses. Small probabilities are overestimated and higher ones are underestimated.

Based on a simulated driving experiment, Katsikopoulos *et al.* (2002) found that drivers' route choice behaviour is consistent with the Prospect Theory interpretations (Bogers *et al.*, 2005). A risk-averse attitude is revealed when choosing among routes with average travel time less than a reference one. Alternatively, a risk-seeking attitude is revealed when the average travel time of alternative routes is more than the reference one.

The contribution of the Prospect Theory of decision making is valuable in shifting modellers' focus from the typical structural-oriented modelling frameworks to the direction of a process-oriented one. Though it is not considered as a process-oriented modelling approach, it represents an essential intermediate ground. It explicitly addresses the uncertainty of the choice environment (i.e. risky). It does not presume rationality of decision makers, reflecting a descriptive modelling approach. However, it still lacks the vital representation of the deliberation time dimension, and, hence, it is static. In addition, a deterministic-type choice constitutes the model output (Busmeyer and Townsend, 1993).

2.3.3 A Vision for Modelling Needs

It is evident that the MET approach to route choice modelling is dominant in the literature. It is equally evident that improving the behavioural credibility of modelling drivers' route choice decisions has been the focus of extensive research throughout the past decade. Although several modelling attempts have departed from the formal utility-maximization paradigm and adopted more behaviourally realistic frameworks, there remains a lack of an explanatory mechanism of the decision process itself. In addition, most of these modelling frameworks adopt a static modelling approach of choice decisions as they fail to account for the direct effect of deliberation times on final decisions. As such, we realize the need for a scientifically sound behavioural decision theory that attempts to abstract the deliberation process rather than focusing on formulating a relationship between inputs and outputs. This need motivates crossing the engineering borders to the behavioural science arena, seeking an appropriate ground for modelling drivers' route selection processes. The target is a theoretical framework with the following properties:

1. **Process-oriented**: reflecting the cognitive process under which decisions are made and evolve over time.
2. **Risky**: reflecting the uncertainty under which drivers make their choices.
3. **Stochastic**: reflecting the high variability of human preferences.
4. **Descriptive:** reflecting a realistic representation of the evolution of individual drivers' decision processes without a normative assumption about their behaviour.
5. **Dynamic**: reflecting the direct influence of the deliberation time on the choice process. This is of significant importance, as most drivers' choice decisions are made under time pressure constraints.

Stern (1998) pointed out the need for a scientifically sound behavioural decision theory for modelling drivers' choices in general. Although he did not develop a mathematical model, Stern proposed this direction for future research. He suggested the investigation of the Decision Field Theory (DFT) to model choices made by drivers in congested networks. DFT, developed by Busemeyer and Townsend (1993), aims to understand the motivational and cognitive mechanism that guide the deliberation process involved in making decisions under uncertainty. DFT provides a formal description of the dynamic evolution of preferences during deliberation. While Stern's (1998) study was not specifically addressing drivers' route choice decisions, it broadly highlighted some of the main factors influencing drivers' choice decisions in general and their implications within a decision-based theoretical framework. The strength of DFT stems from its ability to incorporate all of the above-mentioned characteristics (process, risky, stochastic, descriptive, and dynamic) in a seamless framework. Details of DFT theoretical structure, strengths, and appropriateness to the problem in hand are discussed in the next chapter.

2.4 LEARNING PROCESS

The decision making aspects and the learning aspects of route choice are highly intertwined, both in reality and in the modelling literature. One can think of route choice as perhaps one coin with two sides, a learning process side and a decision making side. To the extent possible, we try to delineate the two processes and understand the aspects of both sides. The preceding section summarized the efforts in the literature that are more focused on the decision making aspect of route choice. To complete the picture, the following section summarizes the efforts in the literature that are more focused on the learning aspects of route choice. As can be expected, there is considerable overlap between modelling the decision making and learning aspects of the route choice process.

2.4.1 Learning Process Overview

Drivers' choices are performed in an uncertain dynamic environment. The dynamic evolution of traffic conditions is realized from day-to-day as well as within each day. Accordingly, choices are contingent upon outcomes from previous experiences. By repeatedly experiencing the same choice situation, drivers learn about their environment, forming perceptions about the values of relevant attributes.

Drivers' learning processes can be divided into two learning horizons: short-term and long-term. Within the short-term time frame, drivers continuously update their perceptions about different aspects of the choice situation. These updates include:

- perception of available alternatives,
- expectations regarding the attributes of those alternatives,
- expectations about the levels of uncertainty in the choice environment,
- perceptions about available sources and forms of information, and
- expectations regarding the accuracy level of available information sources.

The short-term updates are usually performed on two levels: day-to-day and day-specific. From day-to-day, drivers update their historical perception of attributes of the choice situation. This experience is formulated on the basis of the outcomes of their previous-day choices together with the acquired (on the previous day) information-based knowledge of unchosen alternatives (Kaysi, 1992). Drivers' day-specific perceptions are formulated by combining historical perceptions with current ones. Current perceptions are based on unfolding traffic conditions (such as incidents, delays, etc.) as well as day-specific information updates. Day-specific information updates are discussed later in this chapter.

From a long-term perspective, drivers update their choice-related strategies in an attempt to improve their choice outcomes (Arentze and Timmermans, 2005). Within our abstraction of the choice processes, these strategies include:

- Information acquisition strategies
- Experience/Information integration strategies
- Decision-making strategies

Long-term learning is concerned with the formulation of the underlying mechanisms of the abstracted choice processes. Updates, in this sense, refer to major re-structuring of adopted strategies. In other words, while the short-term learning perspective is focused on updating the values of some variables within each of the processes frameworks, the long-term one is dedicated to revising the frameworks themselves.

2.4.2 A Glance at Some Learning Process Modelling Efforts

Modelling the evolution of drivers' perceptions of the choice situation attributes has been the focus of extensive research during the past decade. One of the first modelling attempts was that of Horowitz (1984), where a mean perceived travel cost was estimated as the weighted average of those of previous time periods. Travel time variability was not addressed in this early modelling endeavour. Perception updating in the context of probability theory is traditionally done utilizing the well-known Bayesian approach (Kaysi, 1992; Jha *et al.*, 1998; Arentze and Timmermans 2003a; and Chen and Mahmassani, 2004).

Nakayama and Kitamura (2000a) assumed that drivers learn and reason inductively based on the framework proposed by Holland *et al.* (1986). Their model defines route choices by a set of if-then rules, as in a production system (Newell and Simon, 1972). Learning is represented through genetic algorithm operations. Learning is concerned with updating (revising) the adopted set of rules based on an inferiority indicator. The inferiority indicator is used to evaluate the performance of each rule based on past experiences. Induction implies that a rule that has performed well is a good one.

Peeta and Yu (2004) proposed a framework for updating drivers' perceptions within their hybrid probabilistic-possibilistic route choice model. In their hybrid model, drivers' perceptions of decision variables are represented by a membership function. Drivers' choices are based on a set of if-then rules. As such, the day-to-day updating mechanism is focussed on updating the associated membership functions as well as the adopted if-then rules. Day-specific updates, on the other hand, are concerned with minor adjustments of the weights associated with the adopted if-then rules, based on situational conditions.

Arentze and Timmermans (2003b) proposed a conceptual framework for modelling learning and adaptation, using reinforcement learning. In their model, they assumed that: "individuals may forget about their experience in particular situations as a function of time and the characteristics of the event itself" (Arentze and Timmermans, 2005). The developed reinforcement learning framework is focussed on the evaluation of choice alternatives (i.e., rewards of actions).

2.5 Information Acquisition

Both the decision making aspect and learning aspects of the route choice process rely on having "information" about the road network and traffic conditions. This information can be based on actual experience with the alternatives over time or can be explicitly provided on demand by an exogenous information source. For simplicity, traveler information often refers to the latter type. Advancements in communication technologies continuously offer new opportunities for traffic information provision. The techniques for providing drivers with improved information include Variable Message Signs (VMS), traffic information broadcasting, pre-trip electronic route planning, on-board navigation systems, and electronic dynamic route guidance systems. Information available to drivers, through different information sources, can be divided into three main categories: historical information, current information, and predictive information (Ben-Akiva *et al.*, 1991). Apparently, the most useful type of information, while extremely difficult to obtain, is the predictive type. Predictive information is based on projected traffic conditions, which in turn are dependent on drivers' responses to the provided information.

Drivers' decisions to acquire traffic information depend, to a great extent, on the characteristics of the provided information. Information accuracy and timeliness are the two most important attributes in this regard (Khattak *et al.*, 1991). Kaysi (1992), in his proposed framework for modelling driver-dynamic behaviour, characterizes the driver as "interacting with his choice environment, seeking and acquiring information from various sources, processing this information and then selecting from among available alternatives." Accordingly, the first step for the incorporation of information provision into any route choice modelling framework should be based on a realistic representation of drivers' information acquisition. Drivers must first decide to acquire traffic information before they start processing it. An information acquisition model needs to describe (1) how drivers seek to obtain traffic information, (2) from which sources, and (3) in what form.

Kaysi (1992) suggests that drivers' decisions to acquire external information are dependent on three sets of factors. The first set is concerned with the individual's characteristics, such as processing capabilities, and concern with the optimality of the choice. The second set is related to elements of the choice environment, such as time pressure, current traffic conditions, and difficulty of choice situation. The third set is information dependent, taking into consideration information source reliability, perceived cost of obtaining information, and perceived value of the provided information.

In the route choice literature, most existing modelling frameworks do not pay much attention to modelling drivers' decisions to acquire traffic information. Most existing models with information provision representation are focussed on modelling the integration between experience-based and information-based perceptions (as will be discussed in the next section). However, the availability of traffic information does not guarantee its consideration by drivers. Moreover, the increasing number of traffic information sources, with various information characteristics, manifests the need for further understanding and modelling of drivers' information acquisition mechanisms.

2.6 EXPERIENCE/INFORMATION INTEGRATION

2.6.1 Process Overview

Drivers' knowledge of the network is represented by their perceptions of accumulated travel experiences together with available exogenous information received from Advanced Traveller Information Systems (ATIS) sources. In the context of experience/information integration, many concepts and hypotheses are discussed in relevant literature. Schofer *et al.* (1997) suggest that, even in the presence of information, drivers tend to incorporate their own knowledge and perception of the traffic network in their route choices. Fujii and Kitamura (2000) discussed two experience/information integration related concepts: *state dependence* and *information effect*. The concept of *state dependence* represents the situation in which anticipated travel time for future trips is affected by that of past ones; future anticipation is influenced by anticipation held in the past. On the other hand, the *information effect* refers to the correlation between anticipated and actual travel times under high predictive ability. Nonetheless, a driver's predictive ability is expected to be influenced by the amount and quality of acquired information. It is important also to mention that the ability to predict travel times is bounded, which implies that the information effect may not always be significant (Fujii and Kitamura, 2000).

Lotan and Koutsopoulos (1993) proposed three hypotheses regarding choice behaviour in the presence of information. They mainly differ in the way new information is integrated with existing knowledge. The *simultaneous approach* does not differentiate among the types of inputs that affect the decision process. All the factors that affect the final choice are fed simultaneously into the decision mechanism. No *a priori* distinction between existing knowledge and new information is undertaken. The *two-stage approach* assumes a sequential process. At the first stage, existing knowledge is updated based on acquired information. At the second stage, decisions are made based on updated perceptions. Finally, the *default approach* assumes that a default behavioural pattern exists and is changed only if the new information provided differs substantially from existing knowledge.

2.6.2 A Glance at Some Modelling Efforts

Perception updates, experience-based as well as information-based, are represented in most route choice models through a unified update mechanism. As such, information-based updates are seamlessly incorporated in many Bayesian-based learning models (Kaysi, 1992; and Jha *et al.*, 1998). Bayesian updating is concerned with the estimation of a final level of knowledge (posterior information) based on an initial level (prior information), given the availability of new information (Kaysi, 1992). Assumptions regarding the updating interval, amount of memory recall, and saliency of recent *versus* old experience vary among different models.

Peeta and Yu (2004) investigated the adaptability of their hybrid probabilistic-possibilistic route choice model to incorporate information provision. In their proposed framework, they assumed that drivers are not likely to change their if-then rules or perceptions of choice attribute en-route. However, en-route choice behaviour is assumed to be more sensitive to situational factors. As such, the within-day adjustments are restricted to the weights allocated to drivers' choice-set rules to capture information influences.

Mahmassani and Liu (1999) incorporate information updates in their multinomial probit model of drivers' departure time and route switching decisions. Updates are based on perceived accuracy of disseminated information. Mahmassani and Srinivasan (2003) used a dynamic kernel logit model to estimate the effect of various information-related attributes on drivers' route choice behaviour. Information form (i.e. descriptive, and prescriptive information), correctness and completeness are proven to play a significant role in this regard. A significant difference is estimated between drivers' perceptions of over-estimation errors compared to under-estimation ones.

In the default behaviour route choice model proposed by Lotan and Koutsopoulos (1999), knowledge of traffic conditions is divided into two categories: *old knowledge and new knowledge*. *Old knowledge (OK)* constitutes the drivers' perception before the need to make a route choice decision is initiated. *New knowledge (NK)*, on the other hand, is the data acquired and received afterwards, either through observations or traffic information. The default behaviour is, hence, restated as follows: "Discount old knowledge when it is incompatible with new knowledge, and discount new knowledge when it is compatible with old knowledge." To measure the degree of compatibility between OK and NK, some compatibility measures are defined based on the adopted fuzzy logic framework. Estimated compatibility measures are then used to establish new and old knowledge discount rules through the proposed approximate reasoning route choice model framework.

2.7 A SYNTHESIS OF CONTRIBUTING FACTORS

Based on the published literature on route choice modelling and the literature in behavioural choice modelling, we attempt to create a synthesis of the major factors that affect route choice. The operation of various cognitive processes within drivers' route choice behaviour is influenced by many internal (personal) and external (situational) factors. Considerable research efforts have been exerted to try to capture the main contributing factors in this regard (for example, Antonisse *et al.*, 1989; Kaysi, 1991; Mannering and Barfield, 1994; Khattak *et al.*, 1995; Ayland and Bright 1995; Abdel-Aty *et al.*, 1995; Abdel-Aty *et al.*, 1998; and Peeta and Yu, 2004). Identified factors can be grouped under four main categories: (1) driver characteristics, (2) trip characteristics, (3) choice environment characteristics, and (4) information provision characteristics (refer to Figure 2.1). The following categories of factors are expected to influence drivers' route choice decisions:

1. *Driver characteristics*
    - Demographic characteristics such as age and gender.
    - Socioeconomic characteristics such as income level.
    - Personality profiles such as risk attitude (risk-averse *vs.* risk-seeking attitude).

2. *Trip characteristics*
    - Trip Origin and Destination (OD); different OD pairs entail different levels of network familiarity for a given driver.
    - Trip purpose: recurrent trips such as to work or school *vs.* occasional trips such as for shopping.
    - Trip specific constraints such as arrival time flexibility.

3. *Choice environment characteristics*
    - Traffic network attributes: available alternative routes, characteristics of alternative routes (travel time, length, road type, road hierarchy, pavement condition, complexity, and scenery), and variability of traffic patterns on alternative routes.
    - Situational constraints such as time pressure constraints.
    - Situational conditions: remaining trip length, unfolding traffic patterns, delays, and incidents.
    - Environmental conditions such as weather conditions.

4. *Information provision characteristics*
    - Information source: available sources and perceived cost of each information source (time, effort, and money).
    - Information attribute: information form (descriptive and/or prescriptive), accuracy, completeness, and timeliness.

2.8 SUMMARY

Modelling of drivers' route choice behaviour entails the abstraction of the underlying psychological/cognitive processes. Four processes are considered in this regard: (1) decision-making process, (2) learning process, (3) information acquisition process, and (4) experience/information integration process. The decision-making process is further divided into choice-set formulation and mental deliberation. A choice-set formulation model is concerned with the identification of a number of choice alternatives for the route choice problem. While a large number of feasible alternative routes could be depicted for an OD pair, drivers usually consider a subset of these routes (Khattak *et al.*, 1995). In the literature, choice-set generation models are rarely explicitly specified and are calibrated based on indirect information (Cascetta *et al.*, 2002).

The deliberation process, on the other hand, is addressed in route choice literature from two modelling perspectives: Microeconomic Theory (MET) and Behavioural Decision Theory (BDT). MET represents the deliberation process as a rational evaluation of the economic consequences of different courses of actions. A utility-based modelling framework is adopted for that purpose. Most conventional route choice models lie under the utility-based modelling arena (for example, Daganzo and Sheffi, 1982; Ben-Akiva *et al.*, 1984; Cascetta *et al.*, 1996; and Abdel-Aty *et al.*, 1997). The utility-maximization principle is the most widely adopted decision rule. However, the behavioural credibility of the utility-based modelling frameworks has been repeatedly questioned (Algers, 1998, and Stern, 1998). In an attempt to incorporate a behavioural component within utility-based frameworks, some extensions and modifications are undertaken (such as the bounded-rationality principle proposed by Mahmassani *et al.* 1986).

The need for a behavioural perspective of modelling route choice has been realized by many researchers in this domain. As such, a shift of modelling focus from MET to BDT has been repeatedly proposed. A number of modelling approaches are adopted. One of the major modelling streams, in this regard, is the rule-based one (examples include, Pang *et al.*, 1995; Lotan and Koutsopoulos, 1993; and Nakayama and Kitamura, 2000). The rule-based methodology recognizes the fact that individuals have limited processing capacity. As such, drivers are assumed to base their decisions on a set of simple if-then rules. The adopted rules are based on common sense and intuitive behaviour. Other modelling streams include reinforcement learning, artificial neural networks, and prospect theory interpretations.

Although several modelling attempts have departed from the formal utility-maximization paradigm and adopted more behaviourally realistic frameworks, there remains a lack of an explanatory mechanism of the decision process. Modelling of drivers' choices is mainly perceived from a structural-oriented perspective wherein a relationship is formulated between a set of inputs and outputs without a realistic understanding of the underlying psychological process. The deliberation time dimension seems to have been completely ignored. As such, the need for a scientifically sound decision theory that is: (1) process-oriented, (2) risky, (3) stochastic, (4) descriptive, and (5) dynamic, is evident, which is the motivation of this research.

Drivers' perceptions of the choice situation attributes are continuously updated through learning as well as experience/information integration. Perception updating in the context of probability theory is commonly modelled using a Bayesian approach (for example, Kaysi, 1992; Jha *et al.*, 1998; and Arentze and Timmermans 2003b).

Nonetheless, a number of other modelling approaches have been adopted in route choice literature (for example, Nakayama and Kitamura, 2000; Lotan and Koutsopoulos, 1999; and Peeta and Yu, 2004). An implicit assumption underlying most existing modelling frameworks of drivers' experience/information perception integration is that drivers seek to acquire traffic information. The availability of different information sources, with different service characteristics (cost, accuracy, timeliness, etc.) entail the explicit representation of drivers' information acquisition mechanisms.

Finally, the operations of all abstracted psychological/cognitive processes are significantly impacted by the characteristics of the: (1) decision-maker, (2) intended trip, (3) choice environment, and (4) disseminated information. The assessment of the level of impact of different individual/situational factors is, therefore, important for an enhanced understanding/modelling of drivers' route choices.

3 DFT ROUTE CHOICE MODEL CONCEPTUAL FRAMEWORK

3.1 PRÉCIS

The success of ITS applications depends on the accuracy and reliability of network condition assessment, prediction, information dissemination and control formulation, possibly in real time. The predictive accuracy of disseminated information and formulated control strategies require a realistic understanding and representation of the complex behavioural process of drivers' route choices. This behavioural process is characterized by several interacting sub-processes, at the core of which lies a mental deliberation process. In formulating our behavioural perspective of the dynamic route choice deliberation process, this research has been inspired and influenced by recent advances from the field of psychology and behavioural decision theories. Of particular interest to us is the *time-dependent psychological and mental process of preference evolution in an uncertain and time-pressed choice environment*. Of direct relevance to this perspective is the well established Decision Field Theory (DFT), which forms the theoretical basis for modelling the psychological process underlying drivers' route choice decisions.

DFT, founded by Busemeyer and Townsend (1993), is a dynamic behavioural theory that is mainly developed to capture the psychological process involved in general choice decisions under uncertain conditions. In this chapter, we discuss the rationale behind adopting DFT, and its relevance to the problem in hand. A theoretical background of DFT is presented. The conceptual framework for our route choice decision model is, then, defined.

Three choice situations are discussed that vary in the level of traveller information presented to the driver, namely; no information, descriptive information (congestion states) and prescriptive information (specific route guidance). The no information case is presented first in more detail as a base-case, followed by the modifications required to incorporate information integration. Due to the highly intertwined elements of the theory and resulting model framework, an overly simplified application is presented, not for the purpose of applying the framework but for the purpose of understanding it.

3.2 CONCEPTUAL MODEL SCOPE

Drivers' route choice behaviour is abstracted into a number of interrelated cognitive processes: decision-making, learning, information acquisition, and experience/information integration. The decision-making process is further divided into two stages: choice-set formulation and deliberation. The scope of this research is focused on modelling the deliberation component of the decision-making process.

Deliberation is concerned with the mental process involving the trade-off between perceived attributes of the choice alternatives. Drivers' choice sets are outputs of a choice-set formulation model. Within our modelling scope, no attempt is made for modelling the choice-set generation mechanism. A pre-defined choice set is, however, required as an input for the operation of our route choice decision model.

On the other hand, drivers' perceptions about choice attributes are formulated by integrating experience-based and information-based perceptions. An integration framework is, hence, developed for two traffic information forms: descriptive and prescriptive information. The integration is based on perceived reliability of disseminated information. The specific source of information and the means of information dissemination (e.g. variable message signs, in-vehicle navigation device, etc) are irrelevant to the specifics of the model. Drivers are simply assumed to acquire this information and only focus on how the acquired information is mentally processed. The specifics of the drivers' information acquisition mechanism are not explicitly addressed within our conceptual model.

While information-based perceptions could be formulated in a relatively short time, experience-based perceptions are outputs of a long term learning process. For our current modelling scope, the experience-based perception is assumed to have reached a mature stable state; where drivers' perceive the correct statistics and trends of traffic conditions. No attempt is made for modelling the learning side of drivers' route choice behaviour.

3.3 DFT: BASIC CONCEPT

DFT, founded by Busemeyer and Townsend (1993), aims to understand and explain the motivational and cognitive processes underlying choice decision in uncertain choice environments. The deliberation process is summarized by Busemeyer and Townsend (1993) as follows:

> *"When confronted with a difficult personal decision, the decision maker tries to anticipate and evaluate all of the possible consequences produced by each course of action. For a real decision, a vast number of consequences are retrieved from a rich and complex associative memory process. Obviously, all of these consequences cannot be retrieved and evaluated all at once. Therefore, the decision maker must undergo a slow and time-consuming process of retrieving, comparing and integrating the comparisons over time. No action is taken until the preference for one action becomes strong enough to goad the decision maker into an action."*

DFT provides a formal description of the dynamic evolution of preferences during deliberation. An uncertain (risky) deliberation process, as schematically represented in Figure 3.1, is generally concerned with the choice between alternative courses of actions with uncertain consequences. The available options may differ in one or more attribute, and the values of the attributes depend on the expected state of nature following the choice of an action. The basic intuition underlying DFT is that the decision-maker's attention is expected to fluctuate between different attributes and anticipated states of nature during deliberation in a sequential fashion (Diederich, 1997). Accordingly, the evolution of the decision-maker's preference for each option during deliberation is based on the integration of a stream of comparisons of evaluations of alternative options, based on some attributes, over time.

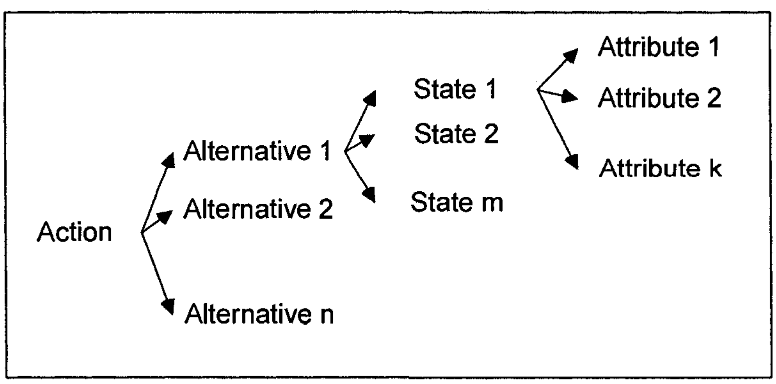


Figure 3.1 Schematic Representation of a General Choice Situation

3.4 PLAUSIBILITY OF DFT FOR BEHAVIOURAL ROUTE CHOICE MODELLING

3.4.1 DFT: a Leading Behavioural Decision Theory

DFT is a process-oriented behavioural decision theory that attempts to abstract the deliberation process based on a realistic representation of the underlying motivational and cognitive mechanisms. The main contribution of the DFT to enhancing the understanding of the psychology of deliberation, as presented by the founders, is depicted in Table 3.1 (Busemeyer and Townsend, 1993). The table provides a classification of decision theories according to two attributes; deterministic versus probabilistic and static versus dynamic. Deterministic theories base choice decisions on binary-type preference relations. A preference relation could be either true or false for any pair of actions. Probabilistic theories recognize the stochastic nature of the deliberation process. As such, choice decisions are based on probability functions, mapping actions' pairs into the closed interval [0, 1]. Static theories ignore the time dimension, assuming that the preference relations or probability functions are independent of the deliberation time frames. Dynamic theories describe the changes in preference relations or probability functions with time. DFT attempts to extend previous decision theories to better capture the probabilistic and dynamic nature of decision making.

Table 3.1 Classification of Decision Theories (Busemeyer and Townsend, 1993)

Category	Static	Dynamic
Deterministic	• Expected Utility Theory • Rank-dependent utility Theory • Prospect Theory [a]	• Dynamics of action [b] • Affective Balance Theory [c]
Probabilistic	• Random Utility Theory	• Decision Field Theory

[a] Prospect Theory is developed by Kahneman and Tversky (1979)
b Dynamics of action is a theory of motivation developed by Atkinson, and Birch, (1970)
[c] Affective balance theory is developed by Grossberg, and Gutowski, (1987)

On the other hand, the strength of a behavioural decision theory could be evaluated based on its explanatory capabilities of central empirical findings from the multi-alternative preferential choice literature (Roe *et al.*, 2001). In this context, three main effects are depicted; (1) the similarity effect, (2) the attraction effect (Huber *et al.*, 1982), and (3) the compromise effect. In the following, a brief description of each of theses empirical findings is presented, (Roe *et al.*, 2001);

1. *Similarity Effect:* produced by adding a new option that is similar to one of the options in the original choice set. This results in a reduction in the probability of choosing the similar option more than dissimilar ones. The similarity effect violates the independence between irrelevant alternatives property, disqualifying the entire class of simple scalable models.
2. *Attraction Effect:* produced by adding a new option that is dominated by one of the other options in the choice set. This causes an increase in the probability of choosing the dominant option. The attraction effect violates a general principle adopted by a large class of random utility models called the regularity principle. The regularity principle implies that the addition of a new option decreases the probabilities of choosing all other options.
3. *Compromise effect:* produced by adding a new option that lies between two competing extreme options. This causes the compromise to be chosen more frequently than either of the extremes.

A number of decision theories have attempted to provide explanations of some of these empirical findings through their theoretical frameworks (Roe *et al.*, 2001). Tversky (1972) developed the Elimination by Aspect (EBA) model to explain the similarity effect. However, the EBA model adopts the regularity principle, and thereby, cannot explain the attraction effect (Roe *et al.*, 2001). Tversky and Simonson (1993) developed a context-dependent advantage model to account for attraction and compromise effects. However, as proven by Roe *et al.* (2001), the model cannot account for the similarity effect. Alternatively, the multi-alternative DFT is the first attempt to account for all three effects within a unified theoretical framework. For a comprehensive analysis of DFT explanations of the three effects as well as their complex interactions, the reader is referred to Roe *et al.* (2001).

Moreover, the superiority of the DFT in modelling the deliberation processes is further illustrated by benchmarking its performance to other well-established decision theories. In a cross-validation type experimental study, DFT is compared to five major theories of decision-making under uncertainty: rank-dependent utility, simple scalability theories, probabilistic regret theory, EBA theory, and random walk choice model (Busemeyer and Townsend, 1993). For each comparison, an important qualitative property is identified to discriminate between the two theories. Results of the comparative analysis favoured the DFT over-all comparison theories. As such, the DFT is identified as a leading decision-making theory in the behavioural science arena.

3.4.2 DFT from a Driver Choice Behaviour Perspective

The dynamic nature of drivers' choice behaviour together with the uncertainty of the choice environment and the high variability of human preferences motivated the adoption of DFT as a theoretical foundation of our framework. DFT offers a sound theoretical ground for modelling the psychological process underlying drivers' choice decisions. Our rationale is based on the following:

- DFT adopts a process-oriented modelling approach that is capable of abstracting the psychological process that inspires drivers' choices. The advantages of modelling the process itself, rather than blindly focussing on the outcomes, are quite evident.
- DFT is developed mainly for explaining and modelling the deliberation process involved in decision-making under uncertainty. As drivers' route choice decisions are often made under high degrees of uncertainty, DFT seems quite appropriate.
- The dynamic nature of DFT reflects its ability to incorporate the direct influence of time pressure in choice decisions. This capability is well-suited to the problem of route choice, particularly under information, as drivers' route choice decisions are usually made under time constraints.

- The stochastic nature of the DFT accounts for the high variability found in human preferences. The need for a shift of focus from the deterministic view of the decision-making process to the probabilistic one is recognized by earlier modelling attempts and is maintained in the DFT approach.

3.5 DFT Theoretical Background

DFT is developed based on psychological principles drawn from two different lines of psychology, approach-avoidance theories of motivation (Atkinson and Birch, 1970) and information processing theories of choice time (Laming, 1968). While DFT was primarily applied to binary choice decisions, it was extended afterward to account for multiple-attribute, multiple-alternative decision-making (Diederich, 1997, Roe *et al.*, 2000).

The theoretical foundation of DFT is presented in a series of seven incremental stages that are mathematically derived from the two mentioned lines of theories. The evolution of each incremental stage stemmed from the development of an enhancement of the previous stage to produce a more general theory. The enhanced theory incorporates a better representation of one or more fundamental properties in the decision-making process (Stern, 1999). The series began with the traditional Deterministic Subjective Expected Utility (SEU) theory, followed by six incremental stages; Random Subjective SEU theory, Sequential SEU theory, Random Walk SEU theory, Linear Systems SEU theory, Approach-Avoidance SEU theory and finally DFT. A detailed description of the development stages is provided by Busemeyer and Townsend (1993).

3.5.1 DFT Basic Theoretical Structure

DFT provides an abstraction of the dynamic evolution of the decision-maker's preferences throughout the deliberation process. The core idea is that the decision-maker sequentially *integrates* comparisons of available options based on different attributes, under different expected states of nature, over time. The deliberation process starts at $t=0$, when the choice situation is presented to the decision-maker and ends at $t=T_D$, when a decision is reached. Choice decision and deliberation time length are direct outputs of the modelled process (Busemeyer and Diederich, 2002).

During the deliberation process, the decision-maker's preference strength toward each option, at any point in time, is denoted $P_i(t)$. The column vector $P(t)$ represents the preference state for all alternative options at time t. Throughout the deliberation process, the evolution of the decision-maker's preference strength toward each alternative, from time t to time t+h (where h is an arbitrary small time unit), is modelled using the following linear difference Equation (Busemeyer and Diederich, 2002; Roe *et al.*, 2001):

$$P(t+h) = S\,P(t) + V(t+h) \tag{3.1}$$

The preference state at z time units could be given by expanding equation 3.1 as follows:

$$P(t) = P(zh) = \sum\nolimits_{j=0,z-1} S^j V(zh - jh) + S^z P(0) \tag{3.2}$$

Where:

1. <u>*Preference state P(t)*</u>: (n*1) column vector representing the preference state at time t. $P_i(t)$ is the preference strength of alternative i (where i= 1 to n, n is the number of alternatives). $P(0)$ represent the initial preference state; a residual bias accumulated from past experiences.
2. <u>*Feedback S*</u>: (n*n) matrix representing the integration factors. The feedback matrix provides memory of the previous preference state for a given alternative as well as the influence of one alternative on another. The Eigenvalues of the feedback matrix are restricted to be less than 1 in magnitude to ensure system stability. Accordingly, the effect of the feedback matrix decays toward zero as the lag increases in value.
    a. **Diagonal elements (self-connections/feedback):** provides memory of the previous preference state for a specific alternative. Having a self-feedback loop allows the preference state of an option to grow or decay over time. A zero value indicates the absence of any memory of previous states. Alternatively, a value of one assumes perfect memory of the previous state.

b. **Off-diagonal elements (interconnections):** captures the influence of one alternative on another. Competitive influences are produced by negative values. A zero value mitigates any competitive influences. In the case where all interconnections values are set to zeros, then alternatives do not compete but rather grow or decay independently and in parallel.

3. *Valance V(t):* (n*1) column vector representing the *momentary* evaluation of the choice situation at time t. $V_i(t)$ represents the momentary advantage or disadvantage of option i in comparison to other options based on the attribute under consideration (where i= 1 to n). The valance vector is composed of the product of three matrices described in Equation 3.3 (Busemeyer and Diederich, 2002; Roe *et al.*, 2001).

$$V(t) = CMW(t) + \varepsilon(t) \tag{3.3}$$

Where:

a. Payoff *M*: (n*r) matrix representing the payoffs of each of n alternatives on each of r attribute/state combinations (r= m states* k attributes, refer to the schematic in Figure 3.1). Each row represents the payoffs for one alternative. Each column represents the payoffs for a specific attribute under a certain state of nature. The payoffs are subjective quantitative values of the perceived attribute-specific gains/losses.

b. Weight *W*(t): (r*1) column vector containing weights corresponding to each column of *M*, representing the joint effect of the importance of an attribute and the probability of a state. The matrix product *MW(t)*, is a vector of weighted average values of each option, based on momentary evaluations at time t.

c. Contrast *C*: (n*n) matrix to compare the weighted evaluations of each option produced by the product of *MW(t)*, (C_{ii}= 1, C_{ij}= -1/(n-1), where n is the number of alternatives).

d. Error term ε(t): (n*1) column vector representing a residual effect of secondary unconsidered attributes.

3.5.2 Distributional Assumptions

An important basic assumption underlying DFT is that the weight vector $W(t)$ changes during the deliberation process according to a stationary stochastic process (Busemeyer and Diederich, 2002). This change represents the fluctuations in the decision-maker's attention to attributes and states over time. While the decision-maker's attention is expected to fluctuate from one state to another according to the anticipated probability of occurrence of each state, the fluctuation in-between attributes is based on a process distributional assumption. Two main assumptions have been proposed in this regard.

The first assumption was proposed by Diederich (1997), who developed a multi-attribute version of DFT. The stochastic changes in weights over time are modelled using a Markov chain process (Busemeyer and Diederich, 2002). For example, assume a choice case with 2 attributes. $W(t)$ is assumed to be a mixture of 2 sub-processes, $W_1(t)$ and $W_2(t)$, which are individually identically distributed (iid) over time. In a route choice context, for instance, a number of alternate routes could be compared on the basis of two attributes; travel time and the number of signalized intersections along the route. At any particular time during deliberation, the attention process may be operating on the basis of one of these sub-processes. Let us assume the decision-maker's attention is focussed on $W_1(t)$, i.e. travel time for example. During the next moment, from time t to t+h, attention either continues to operate under $W_1(t)$ with a probability π_{11} or switches to $W_2(t)$ (number of signals) with a probability $\pi_{12} = 1\text{-}\pi_{11}$. Similarly, if attention is operating on the basis of $W_2(t)$ at time t, then during the next moment attention may continue to operate under $W_2(t)$ with probability π_{22} or switch with probability π_{21}. Based on the Markov chain-process modelling approach, Diederich (1997) presents a detailed mathematical derivation of a closed-form solution from the DFT basic theoretical structure (Equation 3.1).

On the other hand, Roe *et al.* (2001) simply assumed that the weights are identically and independently distributed over time based on a simple Bernoulli process. Accordingly, attention is assumed to shift from one attribute to another in an all-or-none manner based on fixed probabilities (π_1, $\pi_2 = 1\text{-}\ \pi_1$, in the two attributes example). These probabilities reflect the significance of each attribute in the decision-making process.

Thus, at any point in time, the decision-maker's attention is focussed towards only one attribute. For the two attributes example, assume that the decision-maker's attention is focussed on attribute 1. Then, a value is to be assigned to the weight of attribute 1 (based on its units and payoffs significance) and the weight of attribute 2 is to be set to zero. The Bernoulli process is a special case of the more general Markov process. A summary of the mathematical derivation of a closed-form solution based on the Bernoulli process is presented by Busemeyer and Diederich (2002).

Alternatively to the mathematical derivations, the fluctuation in decision-maker's attention in-between attributes could be modelled using computer simulations (Roe *et al.*, 2001). Based on the Bernoulli assumption, and with the incorporation of the anticipated probability of occurrence of different states of nature, a state/attribute combination could be stochastically generated at each time step. Accordingly, at any time point, all entries in the weight vector are to be set to zero except for the one corresponding to the chosen state/attribute combination. Momentary evaluations (valance) and overall preference states could, hence, be estimated from the DFT basic theoretical structure (Equations 3.1 and 3.3).

3.5.3 Decision Rules

Choice decisions are direct outputs of the evolution of the decision-maker's preference strengths over time. Therefore, the length of the deliberation duration up till the decision time is paramount to the process outcome. Decision times could be either externally imposed or internally controlled. Two stopping rules are used in this context; fixed stopping time, and optional stopping time (Roe *et al.*, 2001). Figure 3.2 illustrates the two stopping rules for a hypothetical choice situation between three alternatives (A, B and C).

1- *Fixed stopping time:* the stopping time T_D is predetermined. The preference state is assumed to evolve in an unconstrained manner until a designated time point. At this point the option with the greatest preference value is chosen.
2- *Optional stopping time:* the decision maker determines when to stop according to a preference threshold bound (θ). When the preference strength of one of the options exceeds this threshold, this option is directly chosen. It is noteworthy that

a decision-maker threshold bound is not fixed but rather varies according to the choice situation and time constraints.

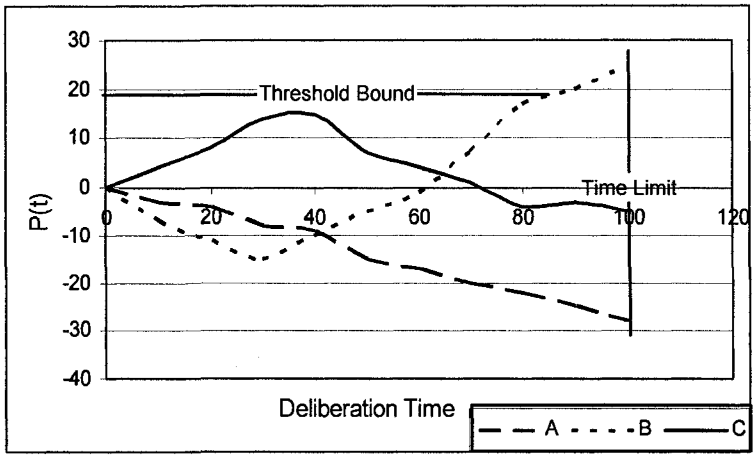


Figure 3.2 Decision Rules of a Hypothetical Choice Situation

As can be drawn from Figure 3.2, deliberation time directly affects the decision process outcome. For instance, if the decision time is externally fixed to 40 (seconds), alternative C would be chosen, which happened to have the highest preference at that instant. If the deliberation process, however, is allowed to mature with no binding external time constraints, preference of alternative B would evolve to exceed the decision maker's preference threshold and hence alternative B would be chosen.

Figure 3.2 is a vivid depiction of DFT in action, illustrating the capabilities of the framework in capturing the decision making process. Under severe time constraints, decision makers can make 'wrong' decisions, opting for an inferior choice at a "high preference" moment. Preference of that inferior choice could be made artificially and momentary high by the choice environment (e.g. using certain sales and marketing tactics to persuade a consumer to buy a certain product). If allowed more time to think and deliberate, a more mature decision may evolve. The characteristics of the decision making process illustrated in Figure 3.2 are of direct relevance to route choice behaviour where drivers often make time-constrained choices in an uncertain choice environment, which is discussed next.

3.6 DFT Route Choice Decision Model Conceptual Framework: Base Case

In this section, the above theoretical framework is applied to establish a behavioural route choice theory and modelling framework. The same framework is adopted for both pre-trip and en-route deliberation processes. The base case of the discussed framework is focused first on a common route choice situation with no explicit traveller information provision. This experience-based deliberation is considered the base case upon which different traffic-related traveller information is later integrated. As such, a "no information" situation is assumed throughout the presented route choice decision modelling framework. Information integration details are discussed after.

3.6.1 Behavioural Route Choice Model Schematic

The deliberation model architecture could be fully described through the definition of three main elements; alternatives, states, and attributes (refer to the schematic in Figure 3.1). For the route choice problem, the following elements are defined.

3.6.1.1 Alternatives

The output of any deliberation process is a choice of a certain alternative among a number of available ones. For the route choice problem alternatives are, naturally, routes connecting an Origin-Destination (OD) pair. For each OD pair, a number of alternative routes are perceived by each driver as tentative ones (whole routes for pre-trip choice decisions and partial ones for en-route choice decisions). As the scope of our route choice model is limited to modelling the deliberation process, candidate alternative routes are to be defined using a separate choice-set generation model. Alternate routes can be defined by the modeller, generated by a simple procedure such as k-shortest paths, or adopting an elaborate route choice set generation procedure such as the one suggested by Cascetta, (2002). In all cases, the pre-defined route alternatives are external inputs to our route choice model.

To ensure a realistic representation of the deliberation process, an upper limit is to be defined for the number of alternative routes in a driver's choice set. There is evidence in the route choice literature suggesting that drivers consider only a small number of alternative routes. The field survey conducted by Cascetta *et al.* (2002) revealed that only a small number of users considered sets with more than two alternatives. Stephanedes *et al.* (1989) found that less than 3% of the commuters in Minneapolis-St. Paul considered more than two alternatives, and if they did, it was under unusual circumstances such as severe weather conditions. Arslan and Khisty (2005) have limited the number of alternative routes to three in their hybrid route choice model. Based on these findings, limiting the number of alternatives to a maximum of three, is considered reasonable.

3.6.1.2 States

The uncertainty of drivers' choice environment reflects a risky choice situation where drivers anticipate a number of possible scenarios and act upon them. As drivers' perception of the choice situation is dependent on the anticipated state of nature following the choice decision, specification of the possible states and their probabilities of occurrence are necessary in this context. Each state has to describe the entire choice situation.

The variability of traffic conditions and states could be reasonably represented through the definition of a number of congestion levels for each alternative route, based on historical statistical data, which are common in practice. Anticipated states are then defined through the combination of anticipated congestion levels for the alternative routes. To limit the possible combinations to a practical number, congestion levels for each alternative route are restricted to a maximum of three coarse levels, high (H), medium (M), and low (L). This coarse categorization is considered to be realistic from a cognitive perspective. It has been proven that there are threshold values for perceiving differences in attribute values (Kaysi, 1992). This implies that individuals can only perceive differences when they are beyond a value referred to as the 'Just-Noticeable-Difference' level.

To further clarify the notion of a state, imagine a hypothetical route choice situation where a driver is to choose between two alternative routes. Assume that two congestion levels are defined for each alternative route (H, and L). As such, four possible anticipated states could be realized (State 1: HH, State 2: HL, State 3: LH, and State 4: LL). Figure 3.3 displays the schematic representation of this hypothetical choice situation.

3.6.1.3 Attributes

During the deliberation process, drivers compare and trade-off alternatives based on expected payoffs of some attributes. Throughout the past decade, extensive research has been focussed on the analysis of factors influencing drivers' route choice decisions. While considered attributes could differ from one driver to another, specification of a set of measurable attributes is obviously essential. Travel time is naturally considered by all modelling attempts as the primary trade-off aspect in route choice decisions (for example: Ben-Akiva *et al.*, 1991; Lotan and Koutsopoulos, 1993; Jha *et al.*, 1998; and Mahmassani and Liu, 1999). However, significant influences are reported for other attributes, namely: travel time reliability, travel distance, route hierarchy, and route complexity (Antonisse *et al.*, 1989; Khattak *et al.*, 1995; Ayland and Bright 1995; Abdel-Aty *et al.*, 1995; and Peeta and Yu, 2004).

Travel time uncertainties are already represented in our modelling framework through the definition of anticipated congestion states and their combinations. Travel distance is an important aspect and is easily quantifiable, and hence, its incorporation as a trade-off attribute is viable. Route hierarchy and route complexity are realized to be very much related. A freeway is mostly perceived to be less complicated than a surface street (fewer turning manoeuvres and no traffic lights). Accordingly, a single attribute is considered for both aspects; referred to as freeway-usage attribute. In sum, for the proposed model, three attributes are considered; Travel Time (TT), Distance (D) and Freeway usage (F), as shown in Figure 3.3 for the case of two routes and two congestion levels.

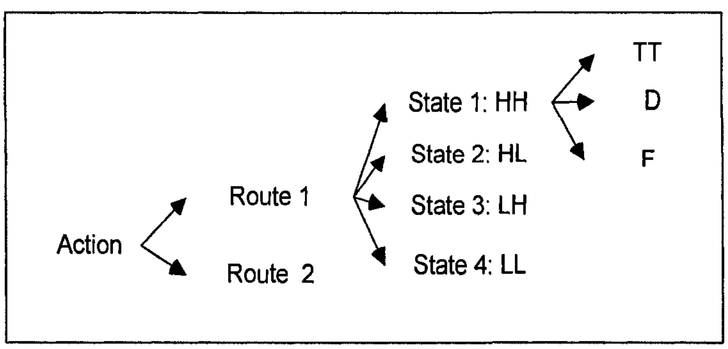


Figure 3.3 Route Choice Model Schematic of a hypothetical choice situation (Base case)

3.6.2 Route Choice Model Decision Variables

Decision variables are simply quantitative representations of the choice situation (independent variables). Two sets of decision variables are required for the operation of DFT route choice decision models; Anticipated State Probabilities (*ASP_i*, i=1 to m states), and attributes' payoffs (*M* matrix in Equation 3.3).

3.6.2.1 Anticipated State Probabilities (ASPs)

Drivers form expectations about anticipated congestion levels for different alternative routes based on previous experiences with the traffic network. A probability value [0, 1] is, accordingly, assigned to each anticipated congestion state. Anticipated congestion states are global states, representing congestion levels of all alternative routes. Obviously, the sum of *ASPs* must sum up to unity

ASPs represent drivers' perception of anticipated traffic conditions. This perception is continuously updated based on day-to-day and day-specific learning. As our modelling scope is limited to the deliberation process, experience-based *ASPs* are assumed to have reached a stable steady state (fixed values) prior to engaging in the current decision process. In the absence of an elaborate learning model, historical statistical data could be used to estimate these probabilities.

3.6.2.2 Attribute Payoffs (M matrix)

Deliberation is a trade-off between different attributes of the choice alternatives. A quantitative representation of expected gains/losses on each attribute is, therefore, required. The payoff matrix (*M*) is formulated based on the payoffs of each considered attribute under each considered state. As the defined states of nature are congestion-based, only TT payoffs are to vary, for the same alternative, from one state to another. Both D & F are unique for each route, irrespective of congestion states. For the hypothetical choice situation between two alternative routes with two congestion levels, the general form of its *M matrix* is as follows;

$$M = \begin{bmatrix} M_{HH/TT1} & M_{HH/D1} & M_{HH/F1} & M_{HL/TT1} & M_{HL/D1} & M_{HL/F1} & M_{LH/TT1} & M_{LH/D1} & M_{LH/F1} & M_{LL/TT1} & M_{LL/D1} & M_{LL/F1} \\ M_{HH/TT2} & M_{HH/D2} & M_{HH/F2} & M_{HL/TT2} & M_{HL/D2} & M_{HL/F2} & M_{LH/TT2} & M_{LH/D2} & M_{LH/F2} & M_{LL/TT2} & M_{LL/D2} & M_{LL/F2} \end{bmatrix} \tag{3.4}$$

The perceived significance of attribute payoffs is expected to vary with trip-specific characteristics. Trip length is a main actor in this context. A 5 minute increase in trip travel time is perceived differently for a 10 minute trip compared to a 1 hour trip. The same applies to the distance and the freeway usage attributes. To account for this significant effect, Relative payoffs are considered for our modelling framework, as follows (where, i denotes an alternative, and j denotes a state);

1. Travel Time Payoff $TT_{ij} = \dfrac{ExpectedTT_{ij}}{TT_{Shortest}}$ (3.5)

2. Distance Payoff $D_{ij} = \dfrac{Map\_basedD_i}{Map\_basedD_{shortest}}$ (3.6)

3. Freeway usage Payoff $F_{ij} = \dfrac{Freeway\_Length_i}{Map\_basedD_i}$ (3.7)

Where

- *Expected* TT_{ij}; represents driver's expectation of trip travel time using route i under congestion state j.
- $TT_{shortest}$; the shortest possible travel time among all alternative routes.
- *Map_based* D_i; Map-based distance length of route i.
- *Map_based* $D_{shortest}$; the shortest Map-based distance length among all alternative routes.
- *Freeway_Length*$_i$; the distance length of the freeway portion of route i.

While specification of the payoffs of the distance and the freeway usage attributes is simply based on the network geometry, this task is more challenging for the travel time attribute. The uncertainties in the route choice decision-making process are mainly related to travel time expectations. The stochastic nature of the choice environment is represented through expectations about travel time gains/losses. Within our modelling framework, travel time uncertainties are captured through the definition of the anticipated congestion states. Learning is, therefore, focussed on updating drivers' perception about the probabilities of these anticipated states. However, specification of an expected travel time for each congestion state is assumed to be deterministic to keep the complexity of the model to a manageable level. As such, expected travel time payoffs, under each anticipated congestion state, are fixed to the mean travel times obtained from field measurements. The minimum of all estimated *Expected TT* values is recognized as the *shortest TT*.

3.6.3 Route Choice Model Decision Parameters

A single modelling framework is adopted for both pre-trip and en route-choice contexts. This entails the same number and structure of decision parameters. Nonetheless, parameter values may differ from process to another. In the following sections, each decision parameter is defined in relation to each choice context.

3.6.3.1 Initial Preference State P(0)

The concept of the usual or normal route is often introduced in pre-trip route choice literature as the one that is chosen most of the time as long as there is no need for divergence (Khattak *et al.*, 1995). Many researchers have viewed the route choice problem from this perceptive, where they attempt to model the probability of divergence from the usual route rather than the choice from a number of alternative routes (Lotan and Koutsopoulos, 1999; and Abdel-Aty and Abdallah, 2004). Coinciding with the usual route concept, DFT route choice modelling framework attempts to handle drivers' intuitive preference toward one of the available options by specifying an initial preference state. This initial preference represents the accumulation of experiences over a long period of time and an underlying learning process. The initial preference state parameter, therefore, is inherently dynamic over long spans of time. However, in the short term, it is not unreasonable to assume the initial preference to be static, at least for modelling purposes. As such, within our modelling framework, drivers' experiences are assumed to have reached a mature steady state.

It is evident that the initial preference concept in DFT nicely captures the usual route concept found in the pre-trip route choice literature. Equally importantly, however, it also captures another key concept known as "inertia", in the en-route decisions context. Inertia mainly refers to the drivers' intuitive tendency to remain on their current route and not to divert unless there is an actual need for divergence (Srinivasan and Mahmassani, 2000). In this sense, and in the en-route decision context, the initial preference concept in DFT is a direct representation of the inertia concept. Drivers are expected to have intuitive bias towards their current route, based on which the deliberation starts. Payoffs expectations have to gradually mount before their preference shifts to alternate routes. This captures the need for compelling payoffs, and deliberation time frames, before a divergence becomes likely.

From a modelling perspective, the initial preference state is a column vector composed of initial preference strengths. Initial preference strengths are quantitative representations of drivers' intuitive level of bias toward each of the available options. Personal factors are expected to influence the set levels of bias. For example, a risk-seeker type driver is expected to have lower attachment to their usual/current routes compared to a risk-averse one. In addition, situational factors such as weather conditions and trip purpose are also expected to play an important role in the drivers' willingness to divert from their usual/current routes.

3.6.3.2 Weight Vector W(t)

The continuously changing weight vector represents the psychological fluctuation in the decision-maker's attention from one attribute to another and from one state to another, during the deliberation process. A Bernoulli-type distributional assumption is adopted to model the fluctuation in drivers' attention (refer to section 3.5.2 for theoretical background). This means that at any point in time, the driver's attention in expected to be focussed on only one attribute under one expected state of nature. Mathematically, this could be interpreted as assigning a value (W_j), where j represents a state/attribute combination, while setting all the other elements in the vector W to a zero value. The assigned value is a reflection of the significance of the payoff of the considered attribute. This entails the specification of an attribute weight for each considered attribute. Attribute weights are simply used for the normalization of the payoffs of different attributes. For the hypothetical example of a choice between two alternative routes with two congestion levels, the general form of the weight vector is as follows;

$$W^T = \begin{pmatrix} W_{HH/TT} & W_{HH/D} & W_{HH/F} & W_{HL/TT} & W_{HL/D} & W_{HL/F} & W_{LH/TT} & W_{LH/D} & W_{LH/F} & W_{LL/TT} & W_{LL/D} & W_{LL/F} \end{pmatrix} \tag{3.8}$$

A computer-simulation approach, based on the DFT basic theoretical structure, is to be adopted for modelling the fluctuation of decisions-makers' attention. Attributes attention probabilities *(π)* are to be used for modelling the switch from one attribute to another. This probability represents the chance of a certain attribute getting the focus at any deliberation time step. Accordingly, attention probabilities for all attributes must sum up to unity. The more important an attribute is to the decision process, the higher its allocated attention probability.

Furthermore, *ASPs* are used to model the fluctuation in between congestion states (refer to section 3.6.2.1 for further details). Thus, at any point in time, only one state/attribute combination is stochastically generated. Only the respective element on the weight vector will retain its attribute-specific value, while the rest will have zero values.

In sum, two sets of decision parameters are to be specified for the weight vector; attribute weights (W_i's) and attribute attention probabilities *(π_i's)*, where i=1 to k considered attributes. Both sets of parameters are expected to be individual-specific. Based on the value of these parameters, the fluctuation of decision-makers' attention in-between states and attributes could be modelled using the adopted Bernoulli-type distributional assumption.

3.6.3.3 Feedback Matrix S

The integration of comparisons of different attributes on different states of nature over time is mathematically achieved through a feedback matrix. The feedback matrix is composed of self-connections (diagonal elements) and interconnections (off-diagonal elements). While the self-connections provide a memory level of previous preference states, the interconnections account for the competitive influence between alternatives. Individual-specific values for the self-connections and the interconnections values are to be specified.

3.6.3.4 Error Term

As no model can include all considered attributes for all drivers, a random component or error term is considered. The random component is a residual term that is assumed to follow a normal probability distribution $N(0,\sigma_\varepsilon)$ (Roe *et al.*, 2001).

3.6.3.5 Termination Parameter

Based on the specifics of the route choice environment, a different stopping rule and the related decision parameter are to be specified. The optional stopping rule is to be adopted in unconstrained route choice decisions. Unconstrained deliberation time frames are mostly common in pre-trip choice decisions, where the deliberation time is internally controlled by decision-makers and extended until one of the alternatives satisfies a preference threshold. On the other hand, in many en-route choice situations, an externally imposed stopping time terminates the deliberation process even before it matures. An example could be approaching a bifurcation point on a freeway, where a decision must be made regardless of the level of maturity of the deliberation process. Accordingly, an externally imposed stopping time rule is more suitable when modelling en-route choice decisions, under time pressure constraints.

For the optional stopping rule, an upper preference threshold bound (θ) is to be defined. The preference threshold (θ) is the level of preference that terminates the deliberation process when reached by any of the available alternatives, i.e., if the driver preference to a given alternative peaks beyond this threshold, the corresponding route is taken, regardless of the length of deliberation time. This bound is expected to be individual-dependent as it may vary according to the driver's characteristics, such as age, gender, and personal profile. In addition, it is also expected to be situational-dependent as decision makers could alter their level of acceptance according to the prevailing conditions, such as weather conditions, and trip purpose. The different levels of individuals' decision thresholds reflect an adaptation of decision strategies based on choice-specific conditions.

3.6.4 Simple Illustrative Example

A simplified, hypothetical, and numerical example of the proposed DFT route choice modelling framework is presented in this section. Application of the framework to the example case of two routes and two congestion levels is used. The objective of this section is to further clarify the basics of the DFT route choice theory and model using a relatively easy to follow numerical example. A driver is faced with a route choice situation, where she has to make a route choice without explicit traffic information. The driver's decision is based on her prior experience and perception of the traffic network.

3.6.4.1 Schematic Representation

Two alternative routes are available to the decision maker to choose from. The anticipated congestion levels on any route are broadly categorized into two levels High (i.e. congested) or Low (i.e. not congested), abbreviate by (H and L). Accordingly, there are four possible states of nature following the choice decision; HH, HL, LH, and LL. The trade-off between the two alternative routes is based on three choice attributes; Travel Time (TT), Distance (D), and Freeway usage (F), as previously discussed. The schematic representation of this choice situation is similar to the example presented in Figure 3.3.

3.6.4.2 Decision Variables

Decision variables are categorized into two sets of variables; the Anticipated State Probabilities (*ASPs)* and the attribute payoff *(M)* matrix. *ASPs* are an abstraction of the driver's experience-based perception of congestion probabilities. For our choice example there exist 4 possible states, as mentioned previously. The following *ASPs* are assumed for illustration;

- $ASP_{HH}= 0.3$
- $ASP_{HL}= 0.3$
- $ASP_{LH}= 0.2$
- $ASP_{LL}= 0.2$

The payoff matrix *(M)*, on the other hand, is a 2*12 matrix (2 alternative routes and 12 state/attribute combinations). The matrix is composed of payoffs of all attributes, under all states of nature, for both choice alternatives. Absolute values of the D and F attributes are estimated from the network geometry. However, for the TT attribute, mean TT estimates are to be obtained for each congestion level. Based on the adopted payoffs representation (Equations 3.5, 3.6, and 3.7), absolute attributes values are transformed into payoffs as depicted in table 3.2.

Table 3.2 Illustrative Example Attributes Values

Attributes		Route 1		Route 2	
		Absolute value	Payoff value	Absolute value	Payoff value
TT	H	20 min	2.00	22min	2.20
	L	10 min	1.00	12 min	1.20
D		1500 m	1.50	1000 m	1.00
F		1500 m	1.00	800 m	0.80

3.6.4.3 Decision Parameters

The following illustrative assumptions are considered for the values of the decision parameters;

1. No initial bias toward any option is pre-assumed; $P(0)= [0\ 0]^T$.
2. The same level of significance of attribute payoffs is considered for all three attributes but with different impact directions; W_{TT}=-10, W_D= -10, W_F=10. Both TT and D attributes are naturally assumed to have a negative impact, and hence, negative weight parameters. However, a positive sign is considered for F, assuming that drivers prefer driving on freeways.
3. Travel time is considered the most salient attribute with attention probability π_{TT} of 0.4, while π_D and π_F are both set to 0.3.
4. For the feedback parameters, self-connections (S_{ii}) are set to 0.95, reflecting a high memory level, which is realistic in choice decisions within short time frames. On the other hand, preferences for each option is assumed to evolve independently, setting all interconnections (S_{ij}, $i \neq j$) to a zero value.
5. The error term $\varepsilon(t) \in N(0, 2)$.
6. For the deliberation model with optional stopping rule, two values of θ are considered for comparison; a high value (θ_1= 25) and a low value (θ_2= 15).
7. For the deliberation model with externally imposed deliberation time frames, two time frames are considered for comparison; a tight time frame (T_D= 15 sec) and a relaxed one (T_D= 90 sec).

3.6.4.4 Deliberation Process Evolution

A step-by-step evaluation of the evolution of the driver's preference is performed, based on the DFT route choice modelling framework. A time step of 1 second is assumed. The following is a summary of the choice situation, in DFT terminologies;

- $P(0) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$
- $C = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$
- $S = \begin{bmatrix} 0.95 & 0 & 0 \\ 0 & 0.95 & 0 \\ 0 & 0 & 0.95 \end{bmatrix}$
- $$M = \begin{array}{c} \\ \\ Route1 \\ Route2 \end{array} \begin{array}{cccccccccccc} \multicolumn{3}{c}{\text{State 1: HH}} & \multicolumn{3}{c}{\text{State 2: HL}} & \multicolumn{3}{c}{\text{State 3: LH}} & \multicolumn{3}{c}{\text{State 4: LL}} \\ \text{TT} & \text{D} & \text{F} & \text{TT} & \text{D} & \text{F} & \text{TT} & \text{D} & \text{F} & \text{TT} & \text{D} & \text{F} \\ \end{array}$$
  $$\begin{pmatrix} 2 & 1.5 & 1 & 2 & 1.5 & 1 & 1 & 1.5 & 1 & 1 & 1.5 & 1 \\ 2.2 & 1 & 0.8 & 1.2 & 1 & 0.8 & 2.2 & 1 & 0.8 & 1.2 & 1 & 0.8 \end{pmatrix}$$
- $ASP_{HH} = 0.3$, $ASP_{HL} = 0.3$, $ASP_{LH} = 0.2$, $ASP_{LL} = 0.2$
- $W_{TT} = -10$, $W_D = -10$, $W_F = 10$
- $\pi_{TT} = 0.4$, $\pi_D = 0.3$, $\pi_F = 0.3$
- $\varepsilon(t) \in N(0, 2)$

The evolution of the driver's preference with time is estimated using Equations 3.1 and 3.3 as follows;

<u>At t=0</u>

$$P(0) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

At t=1

1. Randomly choose a state/attribute combination based on pre-specified probabilities (*ASPs, π's*) → State HH, TT attribute.
2. $W(1) = (-10 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0)^T$
3. $CMW(1) = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} -20 \\ -22 \end{bmatrix} = \begin{bmatrix} 2 \\ -2 \end{bmatrix}$
4. Using Equation 3.3: $V(1) = CMW(1) + \varepsilon(1) = \begin{bmatrix} 2 \\ -2 \end{bmatrix} + \begin{bmatrix} -0.93 \\ -0.4 \end{bmatrix} = \begin{bmatrix} 1.07 \\ -2.4 \end{bmatrix}$
5. Using Equation 3.1:

$$P(1) = SP(0) + V(1) = \begin{bmatrix} 0.95 & 0 \\ 0 & 0.95 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1.07 \\ -2.4 \end{bmatrix} = \begin{bmatrix} 1.07 \\ -2.4 \end{bmatrix}$$

At t=2

1. Randomly choose a state/attribute combination based on pre-specified probabilities (*ASPs, π's*) → State LL, TT attribute.
2. $W(1) = (0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad -10 \quad 0 \quad 0)^T$
3. $CMW(2) = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} -10 \\ -12 \end{bmatrix} = \begin{bmatrix} 2 \\ -2 \end{bmatrix}$
4. Using Equation 3.3: $V(2) = CMW(2) + \varepsilon(2) = \begin{bmatrix} 2 \\ -2 \end{bmatrix} + \begin{bmatrix} 3.1 \\ -1.1 \end{bmatrix} = \begin{bmatrix} 5.1 \\ -3.1 \end{bmatrix}$
5. Using Equation 3.1:

$$P(2) = SP(1) + V(2) = \begin{bmatrix} 0.95 & 0 \\ 0 & 0.95 \end{bmatrix} \begin{bmatrix} 1.07 \\ -2.4 \end{bmatrix} + \begin{bmatrix} 5.1 \\ -3.1 \end{bmatrix} = \begin{bmatrix} 6.12 \\ -5.38 \end{bmatrix}$$

The above process is repeated every second and the evolution of the driver's preference strength is estimated as illustrated above. Figure 3.4 shows an insightful depiction of the mental deliberation process and the resulting preference evolution in the mind of the decision maker. The driver started with no preference bias towards any of the alternatives. Throughout the process, the driver's attention or focus oscillates among the different attributes and their associated payoffs, under the uncertain states of nature. The driver's preference initially oscillates back and forth between the two options before it later matures in the direction of favouring route 1 over route 2. Terminating the deliberation process is either performed by externally imposing stopping time, or by specifying an upper preference threshold.

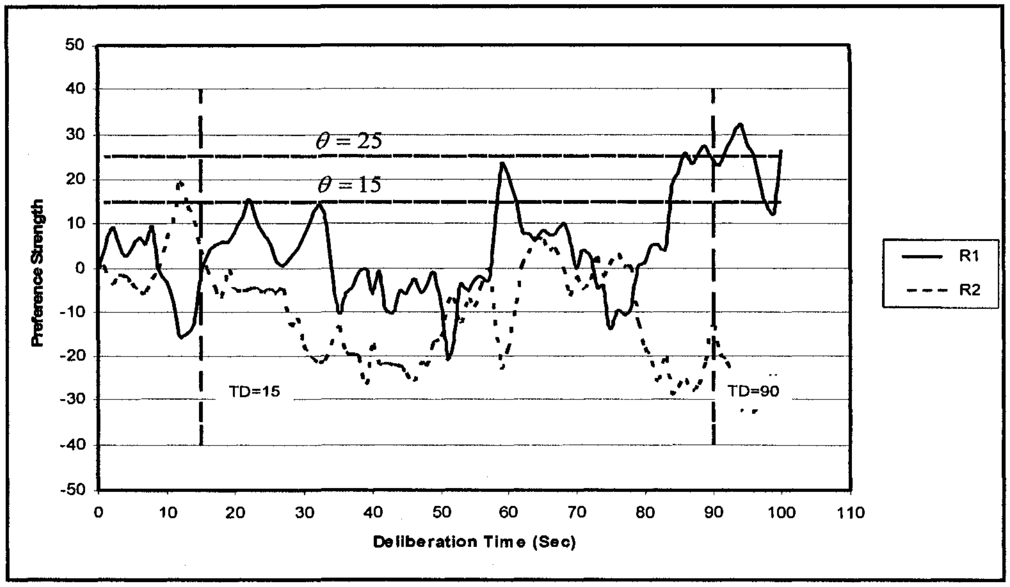


Figure 3.4 Illustrative Example Results

The direct influence of time pressure and preference threshold constraints can be clearly seen in Figure 3.4. A low preference threshold or a short deliberation time frame may result in an immature and possibly wrong decision. Relaxing the time pressure constraint is expected to result in a better, well-informed choice decision. Similarly, increasing the preference threshold assures a better decision, but requires longer thinking time. These simple results reinforce our intuition about the value of the proposed DFT approach for route choice modelling. In real life route choice situations, drivers often make wrong or 'regrettable' route choices, opting for an inferior route at high-preference moment. This situation primarily arises if the decision time is tightly constrained before an impending bifurcation or if the driver's preference threshold is impatiently low. The odds of choosing the wrong route may also increase if the level of uncertainty in the traffic states increases as in the case of unfamiliar drivers. If the driver is allowed more time to think and deliberate and/or if the level of certainty is improved, more mature decision may evolve. One possible way to enhance the quality of the driver's decisions is though the provision of accurate traffic information, which is discussed next.

3.7 INTEGRATION OF TRAFFIC INFORMATION

The success of ITS applications depends on the accuracy and reliability of network condition assessment, prediction, information dissemination and control formulation, possibly in real time. Advanced Traveller Information Systems (ATIS) is an ITS sub-domain that aims to reduce traffic congestion through the dissemination of various forms of traveller and traffic information to drivers. Advancements in navigation and communication technologies are increasingly expanding ATIS possibilities. The usefulness of disseminated information and formulated control strategies require realistic understanding and representation of the complex behavioural process of drivers' utilization of and response to such information. This motivates the incorporation of ATIS in the proposed DFT route choice model framework. For our modelling attempt, two forms of traffic information are considered; descriptive information and prescriptive information. Descriptive information is typically a subjective display of traffic conditions on alternative routes (such as route A moving well and route B moving slowly). On the other hand, prescriptive information explicitly recommends to the driver to take a certain route (such as take route B). The following sections outline how we envision to expand the DFT route choice model to include both types of ATIS.

3.7.1.1 Descriptive Information Deliberation Model

Descriptive information usually gives an overview of current or predicted traffic conditions on various alternative routes. The route choice model architecture for the descriptive information case is conceptually similar to the no information one but with frequent short term updates of the anticipated system states based on the disseminated information. In other words, descriptive information is integrated into the basic DFT route choice model framework by updating the *ASPs* according to information content. Information reliability is expected to play the key role in this updating process. Drivers weight their experience more heavily if they do not trust the disseminated information and vice versa. The following reliability-based weighting scheme (Equation 3.9, where i=1 to m states) is considered for the integration of experience and information perceptions.

$$ASP_i = (1-W_{info}) * (\text{Experience-based } ASP)_i + W_{info} * (\text{Information-based } ASP)_i \quad (3.9)$$

Where;

- *Experience-based ASP;* represents the driver's perception of the possibility of encountering a specific congestion state, based on previous travel experiences (the same probabilities adopted in the base case with no information provision).
- *Information-based ASP;* a binary probability (either 0 or 1), representing the disseminated information content. The congestion state described by the disseminated information takes a probability value of 1, while all other *ASPs* are of zero values. This probability can be further diluted if the driver has low trust in the accuracy of the provided information, in which case the driver assigns a lower value to W_{info}.
- W_{info}; an information weight reflecting the driver's confidence in disseminated information.

In summary, the integration of the descriptive information provision into the route choice model framework is achieved through the manipulation of *ASPs*. This entails the addition of one new decision parameter to the modelling framework; W_{info}. While the driver's confidence in disseminated information is expected to dynamically evolve with time, W_{info} can be reasonably assumed static in the short term. As such, specification of a weighting scheme, within our modelling framework, is based on the driver's current perception of information reliability. Modelling of the evolution of drivers' confidence in disseminated information is beyond the scope of this research.

3.7.1.2 Prescriptive Information Deliberation Model

Prescriptive information could be offered to drivers in the form of explicit advice to take a certain route. Presently, dynamic route guidance is typically based on current traffic conditions. Nonetheless, research in the arena of dynamic predictive route guidance is rapidly evolving, possibly shaping the upcoming generation of route guidance systems. As travel time is the most common attribute in dynamic route choice behaviour, most prescriptive information is based on minimizing travel times either at the user level or system wide. Unlike descriptive information, prescriptive information does not provide drivers with a complete picture of the choice situation. It rather recommends a specific route from the set of alternatives. As such, a different information integration methodology is proposed.

Under prescriptive information, the concept of driver "compliance" is introduced to the route choice process (Srinivasa and Mahmassani, 2000). Compliance is to act according to the conveyed advice. The integration of the prescriptive information provision within our DFT framework is approached from the compliance perspective. Although compliance is an attribute of the decision maker rather than the alternative, one can envisage a 'compliance recommendation' as an attribute of the alternative, to which the decision maker assigns a weight. In other words, only one of the available alternative routes has the advantage or 'attribute' of being recommended by the information source for the driver to possibly comply with. This route-specific advantage is introduced to the modelling framework through the incorporation of a fourth trade-off aspect, named as the compliance recommendation (C) attribute, as shown in Figure 3.5. The payoff of such an attribute is represented through a binary value (1 or 0) indicating whether this alternative is the one recommended by the disseminated information (payoff value of 1) or not (payoff value of 0). Accordingly, an advantage is granted to the recommended route; having a non-zero C payoff value.

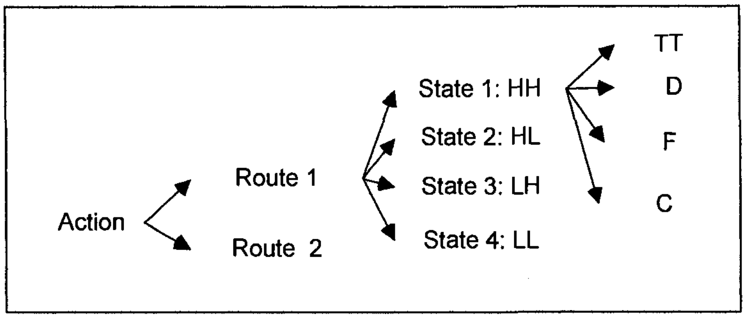


Figure 3.5 Schematic Representation of a Deliberation Situation with Prescriptive Information Provision

The incorporation of a new trade-off attribute in the deliberation process entails expanding the deliberation model decision variables/parameters as well. For the decision variables, the payoffs of the C attribute are to be included in the payoffs *M matrix.* For the hypothetical choice situation between two routes with two congestion levels, the *M* matrix is modified as follows;

$$M = \begin{bmatrix} M_{HH/TT1} & M_{HH/D1} & M_{HH/F1} & M_{HH/C1} & M_{HL/TT1} & M_{HL/D1} & M_{HL/F11} & M_{HL/C1} & M_{LH/TT1} & M_{LH/D1} & M_{LH/F1} & M_{LH/C1} & M_{LL/TT1} & M_{LL/D1} & M_{LL/F1} & M_{LL/C1} \\ M_{HH/TT2} & M_{HH/D2} & M_{HH/F2} & M_{HH/C2} & M_{HL/TT2} & M_{HL/D2} & M_{HL/F2} & M_{HL/C2} & M_{LH/TT2} & M_{LH/D2} & M_{LH/F2} & M_{LH/C2} & M_{LL/TT2} & M_{LL/D2} & M_{LL/F2} & M_{LL/C2} \end{bmatrix} \tag{3.11}$$

The recommendation of one of the routes by the information system has an implicit urge to the driver to comply. However, the driver is not forced to, and hence may not, comply. The driver's willingness to comply depends on many factors including her level of trust in the system's recommendation. The driver, therefore, can assign a lower weight to the compliance recommendation attribute if the system's recommendation is not deemed trustful. This is captured in the model via the incorporation of two additional parameters of the C attribute; attribute weight (W_C) and attention probability (π_C). Drivers' compliance attitude is expected to vary based on their perceptions of the reliability of disseminated information. The variation in perceptions is reflected in the corresponding variation in the values of the compliance-related parameters.

3.8 FROM CONCEPT TO A DFT MODEL

The development of an operational DFT route choice model requires the specification of the model decision variables and decision parameters. Decision variables represent drivers' perception of the traffic network attributes. Within our modelling scope the model decision variables are estimated from the characteristics of traffic network under consideration (network geometry, historical statistical traffic patterns, disseminated information reliability and content).

A crucial step in the development of any operational model is the estimation of the model parameters. Estimation of the parameters of any model is performed on the basis of sample observations from the modelled phenomenon. In the transportation research arena, three types of data are generally considered; stated preferences, revealed preferences, and laboratory experimental data. In stated-preference-type surveys, drivers are asked to state their route choices for an imaginary trip with specific characteristics, given some contextual information (Khattak *et al.*, 1995; and Abdel-Aty *et al.*, 1997). This classical data collection technique is recognized as a simple, cost-effective, and time-saving one. Nonetheless, significant discrepancies between stated and revealed behaviour are increasingly recognized, questioning the credibility of stated-preference-type data (Bonsall, 1993).

At the other end of the spectrum, actual revealed behaviour can be directly monitored through field experiments. Field data could be collected at two levels; aggregate and individual levels. At the aggregate level, route choice trends are estimated from traffic counts. The individual level, on the other hand, focuses on individual drivers recording their choice decisions on a trip-by-trip basis (a log of route choices is maintained). While the credibility of this type of collected data is higher, other important issues arise. Real life route choice decisions are performed in real traffic networks, where we have no control over external sources of impacts on the decision process. Having a wide range of influencing factors is expected to challenge the efforts for identifying the main ones. In addition, in an uncontrolled setting, varying any of the choice environment characteristics is infeasible, and hence, testing the impact of the decision variables is very hard to achieve. Moreover, specific to the DFT route choice modelling framework, choice behaviour need to be monitored at a very fine level. In addition to choice decisions, deliberation times are of paramount interest to us. This entails a precise monitoring of individuals' deliberation processes, which would be very challenging to capture in a real-life setting.

Laboratory simulated route choice experiments have been recognized as a cost-effective route choice data collection technique (for example: Koutsopoulos *et al.*, 1994; Adler *et al.*, 1993; Bonsall *et al.*, 1997; Mahmassani and Liu, 1999; and Bogers *et al.*, 2005). Simulated route choice experiments are mainly computer-based simulations of real life trips. Subjects are recruited to perform route choice decisions for a designed set of experimental trips. As such, the experimenter maintains the required control over the testing setup, in terms of network structure, traffic conditions, information dissemination…etc. Accordingly, the assessment of the impact of various factors is viable, as responses are associated with triggering factors (Koutsopoulos *et al.*, 1994). In addition, in a laboratory environment, detailed observations (such as deliberation time frames) could be easily recorded. From a credibility perspective, based on empirical results, Bonsall *et al.* (1997) concluded that a well-designed route choice simulator could replicate real life route choice attitude with high degree of accuracy. Generally, computer-simulations are perceived to generate near-realistic behaviour, and are thereby, proposed to be used;

- "to simulate real-world decision-making environments, and to record the behaviour of human subjects interacting with this simulated environment,
- to aid in calibrating models of decision-making behaviour, and
- to permit simulations of decision-making behaviour in a large variety of contexts." (Koutsopoulos *et al.*, 1994)

For our purposes of this research, the route choice experiments are envisioned to satisfy the following desirable characteristics:

1. Capture a defined set of personal and situational factors that are expected to influence the route choice decision-making process.
2. Enable the representation of different forms and contents of traffic information.
3. Allow for monitoring and recording deliberation time frames for each choice decision.

4. Be as realistic as possible.

Accordingly, laboratory simulated route choice experiments are recognized as a cost-effective, promising tool for the intended route choice data collection. The laboratory setting offers a high degree of control over the choice environment as well as observed measures. Nonetheless, the realism of the experimental environment and hence the credibility of the observed behaviour need to be properly addressed. The perceived realism of simulated experiments plays a main role in stimulating realistic attitudes, and hence, increasing the credibility of collected data. As such, the next chapter is focussed on the development of a mixed reality simulation environment that enhances the credibility of our simulated route choice experiments. The developed mixed reality simulator combines the benefits of testing human subjects in a driving simulator and the fidelity of detailed network and traffic representation in microscopic traffic simulation platforms.

4 DEVELOPING A LOW COST MIXED REALITY PLATFORM FOR ROUTE CHOICE EXPERIMENTATION

4.1 PRÉCIS

Advances in computing and communication technologies over the past two decades have created ample new opportunities for transportation system modelling and analysis. A number of new tools and methods have emerged that allow fairly complex representation, modelling and analysis of traffic networks. In this chapter, we present the development details of a new low cost mixed reality platform for traffic analysis. The platform is based on two emerging and rapidly maturing technologies; microscopic traffic simulators and driving simulators. Microscopic traffic simulation models offer virtual reproduction of full-scale traffic networks with individual vehicle/driver resolution. Advanced traffic simulators are fairly realistic in terms of the level of the network geometrical details, vehicle characteristics and driving (car following) characteristics. However, relevant behavioural aspects, such as route choice behaviour, are often rudimentary or heavily constrained with theoretical and statistical assumptions. Alternatively, driving simulators allow for direct testing of human subjects and capturing their behaviour and choices. However, the virtual driving environment is typically a fairly rudimentary representation of the road network and traffic conditions, focusing on the immediate surroundings of the test vehicle. To realize the benefits of both traffic simulators and driving simulators, the platform developed in this research integrates both tools to create a mixed reality traffic analysis environment, using very low cost hardware. In such an environment, a human subject can choose and externally "steer" a vehicle that is embedded in a microscopic traffic simulation model of an actual physical network. Using this platform, the realism of actual human behaviour can be captured in an environment that comprehensively reproduces the actual road network configuration and traffic details that the driver can relate to. The objective is to enhance the credibility of in-lab simulated route choice experiments, which is a cornerstone in our route choice model development.

This chapter starts by elaborating on the motivation behind the development of the mixed reality system. Some of the valuable contributions in advancing in-lab simulated route choice experimental tools are then highlighted. Next, we discuss the development details of the mixed reality platform in terms of requirement analysis, system architecture and system implementation. Finally, the capabilities and limitations of the developed platform are summarized. Software development and programming assistance was provided by the Toronto ITS Centre (refer to Talaat *et al*, 2008).

4.2 MOTIVATION

Microscopic traffic simulation emerged more than two decades ago, but recently reached unprecedented levels of maturity, sophistication and usefulness. Advanced microscopic traffic simulation could be considered a breakthrough in modelling traffic at very high levels of resolution. Individual vehicles/drivers are modelled with temporal resolution of a fraction of a second and spatial coverage of hundreds of square kilometres of dense networks. Central to the operation of a microscopic traffic simulation model are several sub-models, most notably, a car-following, a lane-changing and a route choice model. Assumptions underlying drivers' response, rationality and cognitive behaviour, among other factors, directly impact the performance of these models and hence the accuracy of the overall micro-simulation model (Miska *et al.*, 2004). Thus, increasing the behavioural credibility and realism of such models would enable a virtual reality reproduction of mixed traffic in a road network.

Driving simulators are mainly developed to expose human subjects to a realistic driving experience in terms of visualization, motion, and reaction inducing stimuli, all in a controlled and safe off-road environment. Driving simulators are recognized as a useful data collection technique in two main research domains; road safety research and ITS applications. A wide range of driving simulators is commercially available for these types of analysis with varying levels of sophistication and cost (for example: Simcreator, 2007; DriveSafety, 2007; Autosim, 2007; and Scaner2, 2007). In its simplest form there are the game-type Personal-Computer-based simulators with or without a steering wheel. On the higher end of the spectrum, driving simulators can utilize full-fledged vehicle cabins resting on a mobile base and equipped with high resolution virtual reality visualization technologies. The mobile base replicates the motion sensation of a real vehicle for the driver to be fully engaged in the driving experience both bodily and visually. A number of research institutes currently host high-fidelity driving simulators with full-reality interfaces (for example: University of British Columbia, 2007; University of Guelph, 2007; University of Leeds , 2007; and University of Iowa, 2007).

Although driving simulators can excel in replicating the immediate environment of the subject vehicle, they are usually very limited in replicating realistic traffic networks of the size and detail level that microscopic traffic simulators could achieve. In most commercially available driving simulators, the representation of the road network is usually fairly rudimentary and focussed on the immediate surroundings of the subject vehicle. The surrounding environment is restricted to one of a few predefined hypothetical environments such as "urban," "rural," "freeway" "arterial" and so on. The movement of the surrounding traffic is also scenario-based such as "light traffic," "heavy traffic," "cars only," "cars and trucks," etc. The designer of an experiment selects both the broad nature of the surrounding environment and the density of traffic surrounding the subject vehicle. Therefore, only fairly fictitious scenarios could be tested due to the lack of a realistic representation of a full-scale real-life traffic network with properly calibrated realistic traffic conditions.

Neither microscopic traffic simulators alone nor driving simulators alone are adequate for certain complex ITS research topics. For instance, route choice decisions are significantly influenced by the very specifics of the surrounding environment, most notably, the realism of both the driving experience and the network being navigated through. As such, testing drivers' attitudes towards ITS applications such as Advanced Traveller Information Systems (ATIS) is a major research arena that requires testing of human subjects in a "mixed reality environment." Mixed reality, in our context, means a testing environment that has three main features: [1] a real human subject making route choice decisions in response to the perceived environment, [2] ability to execute the decisions, such as changing route using a steering device, and [3] realistic driving episodes such as a typical morning commute in an existing real town surrounded by typical congestion levels. To realize these features, we integrate a driving device into a microscopic traffic simulator. In such a mixed reality environment, actual human subjects can experience a driving experiment in a driving simulator-type environment, while all surrounding roads, traffic levels and congestion evolution are modelled and controlled using a microscopic simulator in a full-scale network model. The objective is to enable credible evaluation of route choice behaviour under various ITS applications.

In summary, micro-simulation models offer detailed reproduction of full-scale traffic networks but lack the "behavioural realism" of actual human drivers. On the other hand, driving simulators use human subjects but lack "traffic realism." Establishing a two-way link between a traffic simulator and a driving simulator is realized to gain the best of both environments. From the specific perspective of route choice analysis, the realism of the choice environment is expected to play the largest role in stimulating realistic route choice behaviour under time pressure and uncertainty of the decision inputs and consequences. The uncontrolled evolution of traffic conditions within the real-time microscopic simulations contributes to enhancing the realism of the simulated choice environment. The impact of a single driver's response on the evolution of traffic conditions will likely be insignificant. However, the real-time evolution of traffic conditions around the driver enhances the realism of the driving experiment. In addition, the developed platform is intended to be generic enough to enable the concurrent testing of multiple drivers in future extensions.

The scope of this work is limited to vehicle routing control. No attempt has been made yet to control driving tasks such as acceleration and braking which are left to the car-following model of the microscopic simulation model as will be explained later in this chapter. It is noteworthy that the consequences of the driver's decision depend on the characteristics of the network, the prevailing traffic conditions, and the driver's familiarity with both (amongst other factors of less relevance to our scope).

4.3 Background of Experimental Route Choice Simulators

Over the past two decades, researchers have recognized the capabilities of laboratory simulated route choice experiments as a non-traditional data collection technique to evaluate the effectiveness of ATIS. Thus, efforts on the development of such experimental simulators have been increasingly significant. While it is not feasible to discuss all of these valuable contributions within our premise, some of the main streams of efforts are briefly highlighted.

One of the early attempts of an in-lab simulated route choice experiment involved the development of an interactive route-choice simulator IGOR, at the University of Leeds (Bonsall, 1991). IGOR runs on a personal computer where subjects select and update their routes at successive isolated intersections. Only a plan view of the intersection and some contextual information are provided to the subject, with no representation of surrounding traffic. IGOR provides subjects with feedback in the form of engine sound with duration proportional to the time required to traverse the chosen link and a pitch proportional to the traversing speed. As successors to IGOR, TRAVSIM and VLADIMIR are both PC-based route-choice simulators, developed, at the University of Leeds (Firmin and Bonsall, 1996; and Bonsall *et al.*, 1997). Both simulators exhibit enhanced functionality on top of the base one. Koutsopoulus *et al.* (1994), developed a PC-based driving simulator, with a 2-D graphical user interface, to test drivers' behaviour in response to traffic information. Abdel-Aty and Abdalla (2004) used OTESP, an interactive windows-based travel simulator as a data collecting tool to investigate drivers' divergence behaviour from their normal route. Another valuable contribution in advancing laboratory experimental route choice simulations is a dynamic multiple-user interactive route choice simulator, developed on top of the mesoscopic traffic simulator DYNASMART (Chen and Mahmassani, 1993). The uniqueness of this simulator stems from its ability to handle multiple users in real time in a dynamic environment. Along the same line of research, many route choice simulators with different levels of sophistication in terms of their user interface and network representation have been developed (for example: Vaughn *et al.*, 1993; Iida, 1992; and Kantowitz *et al.*, 1995). Realistic traffic networks with advanced visualization techniques contributed to a more realistic reproduction of the choice environment adding credibility to the quality of collected data. However, the macroscopic representation of traffic conditions and the lack of a visual display of surrounding traffic limit the simulation experiment to a set of choice decisions rather than a fuller driving experience.

Along a parallel stream of efforts, some advanced route choice simulators offer participants a graphical display of a simulated driving experience with a representation of surrounding traffic. FASTCARS, is an interactive PC-based simulator that is designed to collect route choice data in a game setting (Adler *et al.*, 1993). The simulated trip is graphically displayed through a bird's-eye view of the test network. While surrounding traffic scenarios are pre-specified and limited to the vicinity of the subject vehicle, the microscopic graphical display of individual vehicles offers participants a more tangible representation of congestion scenarios. Another similar contribution is a simulation experiment conducted in Europe to assess the impacts of in-vehicle navigation systems (Ayland and Bright, 1991). A computer game is used for experimentation providing a 3-D display of the traffic network with fictitious representation of surrounding traffic. Drivers are to control the movements of their vehicles using a game-type joystick. Researchers at Delft University of Technology developed TSL, an interactive traveller simulator that is designed to capture adaptive travel choices (pre-trip and en-route choices, departure time choices, the decision to acquire traffic information...etc) (TSL, 2007). An accelerated operation reduces the experiment duration, allowing for an increased sample size of observations within a limited experimentation time frame.

While the aforementioned valuable contributions differ in their level of sophistication and representation of the choice environment, they all lack the desired integration of human subjects, full-fledged networks, realistic traffic, and their microscopic interactions. The potential of the intended integration has been recently recognized by some researchers for various ITS-related applications. Jenkins, M. and Rilett (2005) attempted to develop a two-way communication channel between two commercially available traffic and driving simulators. VISSIM, microscopic traffic simulation software (VISSIM, 2007), was integrated with DriveSafety driving simulator (DriveSafety, 2007). The interaction between the two sides required a two-way real time exchange of information between both simulators. Communication delays reportedly precluded the development of the required two-way communication; however, a one-way communication flow of information was established. Data are sent from the traffic simulator to the driving simulator to control the generation and movements of surrounding vehicles; however, the driving simulator maintained primary control over the subject vehicle. Maroto *et al.* (2006) developed a real-time microscopic simulation model that is specially designed for use within a driving simulator environment. Nonetheless, the simulation is limited to a reduced zone in the vicinity of the driven vehicle. Sarvi *et al.* (2004), integrated a driving capability into FMCSP, a simulation model of freeway merging behaviour. The developed system, enables testing of a driver's merging behaviour in a simulated freeway merging environment.

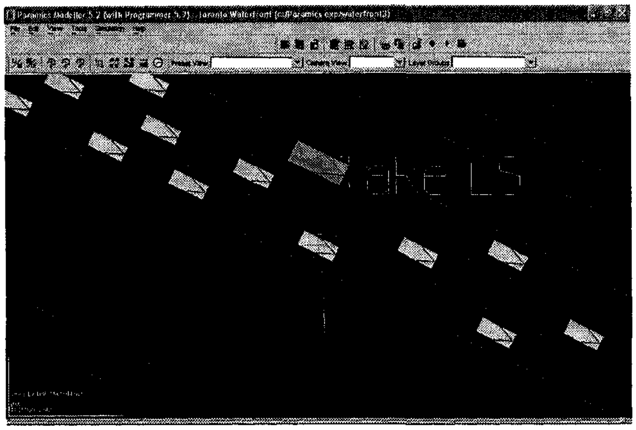
4.4 MIXED REALITY SYSTEM OVERVIEW

Our objective is to integrate a driving tool in the form of a steering system into Paramics, a commercially available and widely used microscopic traffic simulator (Paramics, 2007). Paramics is a suite of high performance cross-linked traffic models that interact to simulate traffic systems behaviour in virtual replicas of physical roadway networks. Paramics models traffic microscopically at the individual driver/vehicle level utilizing a set of interacting sub-models such as car-following, lane-changing, gap-acceptance, and vehicle routing models. Paramics Programmer offers users access to lower level aspects of the traffic network and most of the simulation related sub-models through an Application Programming Interface (API). The API allows the modeller to design and code "plug-ins" that implement a typical tasks such as override default vehicle behaviour or provide context-sensitive information to the driver.

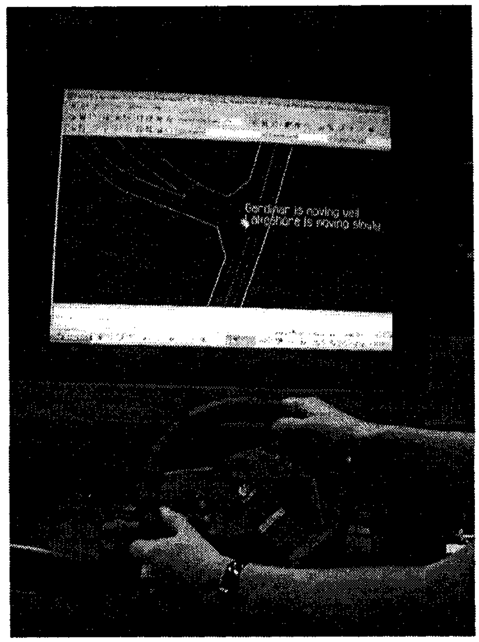
The developed system enables a driver to externally control the *lateral* and *routing* movements of a single vehicle of choice (driven vehicle) in a simulated network using a PC-input device such as a steering wheel, Figure 4.1. Longitudinal control of the driven vehicle, as well as control of all other vehicles are both internally controlled by Paramics. This system enables realistic assessment of the human subject's route choice behaviour in response to ATIS, while driving in a virtual replica of an actual traffic network characterized by uncertainties, complex interactions and time pressure constraints.

4.5 REQUIREMENT ANALYSIS

This section describes the requirement analysis phase of the low cost mixed reality platform, i.e. what needs to be developed, why, and the best approach to do so. Subsequent sections will describe how the required components are developed.



a) Simulator/Driver Interface
(Driven vehicle identified by a circle on top)



b) A Steering Manoeuvre within the Mixed Reality System

Figure 4.1 Mixed Reality System in Action

4.5.1 Input-capturing from an External Device

In reality, drivers' routing decisions are translated into "actions" through the manipulation of a steering wheel. For our mixed reality system, the main input device is an external steering wheel which is used to control the lateral movement of the driven vehicle within the virtual road network. For this external "action" to be depicted by the micro-simulator, an input capturing (IC) application is required to facilitate the flow of external control from attached input device to Paramics.

The most direct implementation of an IC application for our driving system is perhaps through the development of an IC Paramics API plug-in. This approach, however, was deemed unfeasible and was hence precluded due to the following reasons: Paramics API plug-ins are C-based DLL files, allowing the developer to use only Paramics API or Windows API. Paramics API does not provide functions that could enable the direct manipulation of externally attached devices. On the other hand, while Windows API does provide the capability to manage inputs from external input devices, it uses an asynchronous input model to handle these inputs. Windows interrupt handler converts interrupts (such as keyboard inputs) from various input devices into messages and sends them to the appropriate application to be stored into its message queue. In each application, a message loop goes over all messages in its message queue, translates them and then dispatches them to all its windows. Each of the application windows, then, executes the conveyed message through a local window handler, referred to as a window procedure. As such, in order to use Windows APIs to handle inputs from input devices, we need to overwrite Paramics window procedure, which we have no access to. Accordingly, a separate *stand-alone* IC application has to be developed outside Paramics to handle input devices.

4.5.2 Vehicle Control and Traveller Information Display in Paramics

Unlike all vehicles in the simulation model which are internally controlled by Paramics, the driven vehicle has to be externally controlled. Overriding Paramics routing model for the driven vehicle is the main task to be achieved through the development of a "vehicle control" Paramics API plug-in. The vehicle control plug-in receives subject routing directions from the IC application and acts upon them. This "act" is simply a lane change or a turning movement of the driven vehicle in the virtual traffic network, according to the driver's routing choice.

Assessment of drivers' responses to ATIS is one of the main research applications that motivated our development of this tool. Therefore, controlling traveller information/guidance provided to test subjects during the simulation is another task to be manipulated through Paramics API plug-ins. Accordingly, an "information provision" plug-in, that could identify network conditions and disseminate respective descriptive/prescriptive information to test subjects, is required.

4.5.3 Inter-Process Communication

The development of a separate stand-alone IC application outside Paramics requires an Inter-Process Communicator (IPC). IPC regulates the flow of information from IC application to Paramics in a timely manner. IPC consists of shared memory that is visible to both applications and an interface. Since Paramics plug-ins are programmed in C and the IC is coded in object oriented C++, two different interfaces are to be developed. The first interface, written in C++, takes input from the IC application and stores it in the shared memory. The second interface, then, reads inputs in the shared memory and passes it to the Paramics vehicle control plug-in.

4.5.4 Graphical Display to the Driver

The final requirement of our driving tool is the graphic representation of the road network, general traffic and the particular driven vehicle. Paramics provides many simulation visualization options such as plan view, 3D view and in-vehicle view. Thus, the only missing features are the on-screen identification of the driven vehicle to the driver controlling the steering wheel and tracking this vehicle on display as it progresses through the network. These features are to be added to the default Paramics graphical display system. These added features can be easily handled by developing another Paramics API plug-in - a graphical display plug-in.

4.6 SYSTEM ARCHITECTURE

The designed system architecture is based on three basic components that have been identified in the requirement analysis phase; Input Capturing (IC), Inter-Process Communicator (IPC), and several Paramics API plug-ins. The designed system architecture is depicted in Figure 4.2. At each simulation time-step, which is user-specified in Paramics, the system progresses through a sequence of events. First, the IC reads the driver's input from the steering device and translates this input into simple action code (move right, move left or do nothing). Second, the IC commands the IPC to write this input in the shared memory that is accessible to both the steering device and the traffic simulator simultaneously. Third, a Paramics API plug-in commands the IPC to read the action from the shared memory. IPC reads the input and sends it to the API plug-in. Finally, the API plug-in overrides the default lane-changing and route-choice algorithm of the subject vehicle, changes the driven vehicle position on the road and displays the new position on screen. As the driver is navigating and progressing through the network, the system displays different forms of traveller information. Information is generated by an "Information provision" API plug-in.

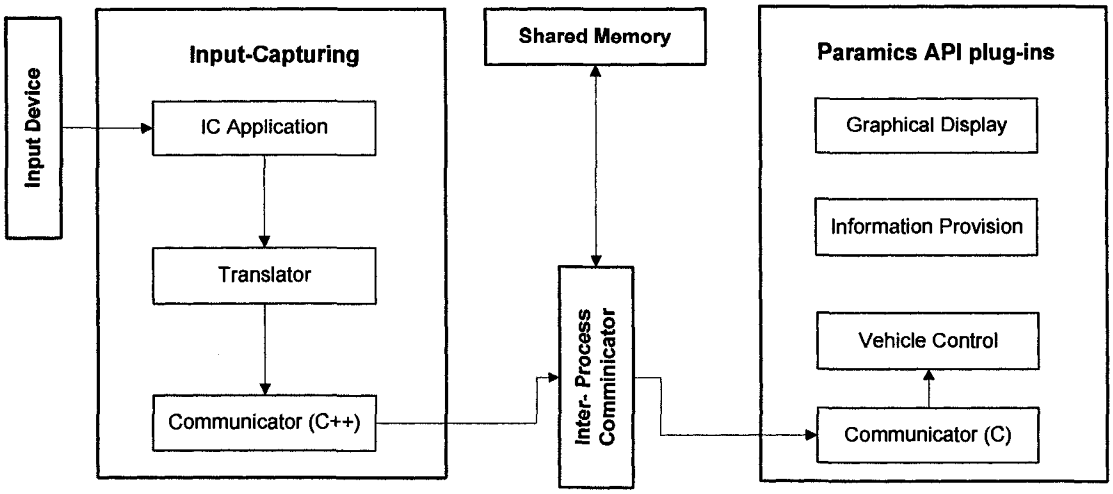


Figure 4.2 Mixed Reality System Architecture

4.7 SYSTEM IMPLEMENTATION

4.7.1 Input Capturing

The input-capturing component is further divided into two sub-components: an IC application and a translator. While the IC application is concerned with depicting any external act from the attached input device, the translator is concerned with interpreting this act into a routing direction. Details of the development and operation of these two sub-models are presented next.

4.7.1.1 Input-capturing Application

The IC application is a set of objects and functions that translate an external act on an attached input device to one or more numeric values. These values can be binary values in case of a keyboard-input device or a continuous number in case of a steering wheel, ranging from -1 at the most left to +1 at the most right and so on. To facilitate the development of this type of application, Microsoft's standard protocol for communication with input devices was used.

DirectInput Library, developed by Microsoft, is the most widely used library that enables direct communication between input devices and operating systems. A DirectInput implementation consists of a tree of objects. At its root, the "DirectInput Object" supports the IDirectInput8 Component Object Model (COM) interface. Only one

Direct Object is to be defined for each IC application. For each externally attached device, a "DirectInput Device Object" is consequently defined. Each DirectInput Device Object in turn has some device specific-objects, which are individual controls or switches such as keys, buttons and axes.

DirectInput works directly with the input device, and as such, it either suppresses or ignores Windows/Operating System mouse and keyboard messages. It also ignores mouse and keyboard settings made by the user in the Control Panel. It does, however, use the calibration set for a joystick or other game controller. This main feature ensures the speed and accuracy of the readings from input devices.

After creating a DirectInput Root Object, enumeration of devices is performed for both the keyboard left and right keys as well as the steering wheel game-type device. As such, test subjects have the option to choose either of these two input devices. In each simulation time step, values of DirectInput Devices' individual objects are updated based on external acts. For the keyboard device, a value of plus or minus 1 is assigned to the pressed key in the keyboard device. While for the steering wheel an axis value ranging from -1 for the most left to 1 for the most right is updated.

The operation of the IC application is actually more challenging than it first seems. This is due to the fact that the IC application must continuously receive inputs from the attached device even if the IC application window is not the active window. This is simply because the simulator's window is always the active window while the subject is driving. Therefore, a so-called "SetCooperativeLevel" function is used to set the IC application focus to the back end. It is worth mentioning that this kind of solution must be handled with extreme caution because it violates the security rules of the operating system (interacting with a window other than the front-active one).

4.7.1.2 Input Translator

Outputs from IC applications are then processed by a translator to determine a movement direction. Only one of three movement directions are depicted, either move right, left or do-nothing. This coarse categorization of movement directions is then manipulated by the vehicle control plug-in to fine tune the respective routing decision.

The translator task is trivial for the keyboard left and right keys device, but the driver's sense of driving might not be as realistic as on a steering wheel. As for the steering wheel-type device, the axis range is categorized into three sub-ranges for each direction of movement. The translator's task is simple enough that it could have been incorporated into the IC application. However, a stand-alone sub-component is useful in the long term for future research; if and when longitudinal control of vehicle speed and acceleration is required.

4.7.2 Three PARAMICS API Plug-ins

4.7.2.1 Vehicle Control Plug-in

Paramics API is used to override internal default routing sub-models, allowing external control of the driven vehicle's routing decisions. At the beginning of each simulation time-step, one of three possible user inputs are obtained from IPC; turn right, turn left, or do nothing. Using a simple algorithm, Figure 4.3, the driven vehicle is allowed to change its current lane or link in the graphical display of the virtual traffic. The algorithm is designed to capture and display users routing decisions. A simple lane-changing logic is adopted just to allow for the execution of routing decisions. The algorithm is based on the ability of the driver to fine-tune her/his routing directions through the display of her/his next exit number, prior to turning. Exits, at each intersection, are numbered in an anticlockwise direction.

To avoid confusing routing steering actions and unintended wheel steering, link change decisions are restricted to a "decision zone." The decision zone is a pre-defined distance upstream of each intersection where the driver is expected to make his route decision; i.e., next-link decision. If the user is outside the decision zone, the steering manoeuvre is simply ignored. Decision zones are long enough so as not to interfere with the deliberation process.

The main challenge facing the development of the vehicle control plug-in is handling the "do nothing" input scenario within the "decision zone." One of the trivial interpretations of the "do nothing" input could be simply "move straight," just like in real-life driving experiences. However, Paramics APIs provide no access to the network geometry and thus depicting a "straight" exit in a complex traffic network is difficult to achieve. In addition, in an experimental setting, a "do nothing" input could be, alternatively, interpreted as an unwillingness to divert from the current route, regardless of its alignment. As such, our mixed reality system adopted what we call "default-route benchmarking." Prior to starting a simulated driving experience, drivers are to specify a set of possible alternative routes to their destination. These routes are marked by our system as "tentative default routes." While drivers proceed from one link to another, their current route is continuously identified by the system and marked as the "current default route." When approaching an intersection, the next exit of the current default route is initially marked for turning. Left and right turning movements are referenced from the default exit.

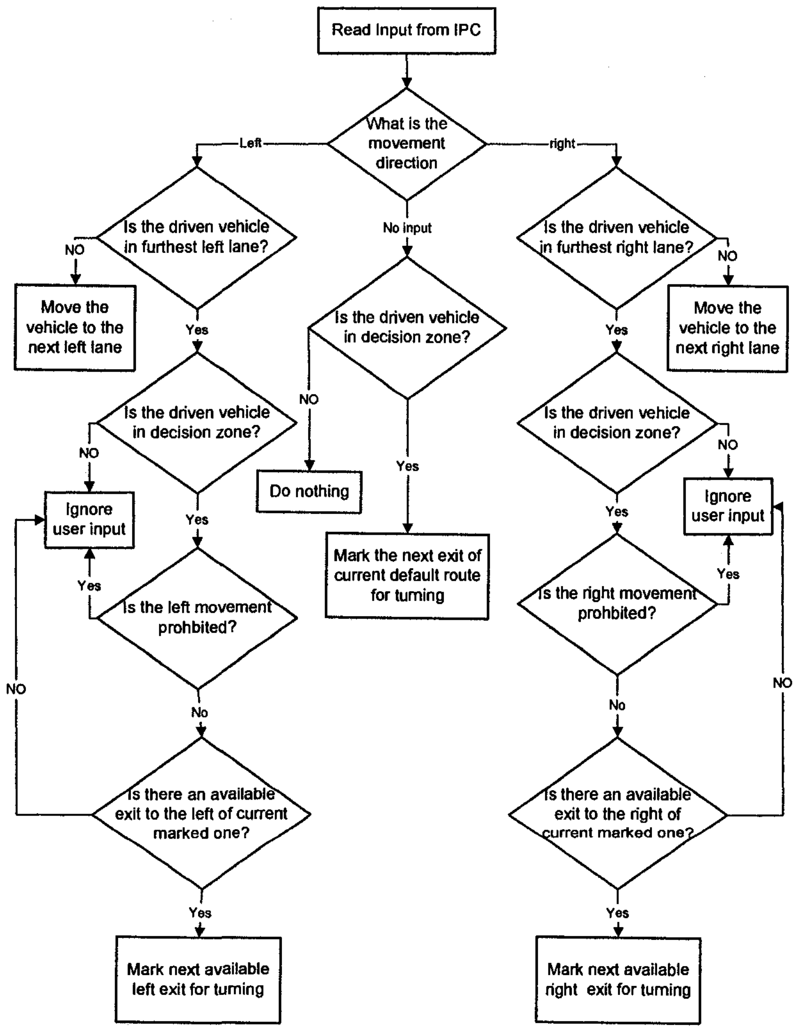


Figure 4.3 Vehicle Control Algorithm

4.7.2.2 Traveler Information Provision Plug-in

A simple information provision interface is developed to generate and disseminate traffic condition information and guidance to subjects while driving. The type of disseminated information and its accuracy are user-specified. Descriptive information provides test subjects with quick reports on traffic conditions on all alternative routes; using high-level description such as route x moving well, route y moving slowly…etc. On the other hand prescriptive information recommends the current fastest route to the subject's destination in an explicit manner. Guidance is provided to the drivers in the form of a text message that appears on the simulation window beside the driven vehicle. The accuracy of the disseminated information can be manipulated through the specification of a variable reliability level. The specified reliability level is interpreted by our system as a probability of providing correct information to the test subject. Other types of messages such as status and warning messages are also provided to the subjects during the simulation.

4.7.2.3 Graphical Display Plug-in

A bird's-eye view window focussing on the driven vehicle and its close vicinity is displayed to drivers. To avoid visualization confusion of the driven vehicle with surrounding traffic, our system identifies the driven vehicle with a circle drawn on top of the driven vehicle itself and moves along with the subject vehicle during the entire simulation.

4.7.3 Inter-Process Communicator and Shared Memory

A shared memory protocol along with an inter-processes communicator is designed to allow the IC application and Paramics plug-ins to link to each other properly without communication delays. Two separate interfaces are required for the implementation of IPC; one written in C++ at the IC application end and the other written in C at the Paramics plug-ins end.

Typically, each process created in Windows has its own local memory. This local memory holds process-specific data/variables that are not accessed by any other process. Alternatively, when a process wants to communicate with another, a common area in the memory called shared/global memory is created. This global memory is referred to in

Windows, as HANDLE. In order to ensure the integrity of shared data, concurrent access to shared data should be restricted. This means that at any point in time, only one process is given access to the shared memory. As such, kernel provides a mechanism, called "mutual exclusion" or "mutex object," to ensure exclusive access to the shared memory resource. Using a mutex object, each process has to follow three steps to access the shared memory. First, it has to hold the mutex object; locking the shared area. Then, it writes/reads data to be communicated into the shared area. Finally, it has to release the mutex object to allow other processes to access the shared area.

In our system, a shared memory is developed to facilitate communication between the IC component and Paramics plug-ins. The CreateFileMapping Windows API is used to create the HANDLE in a certain location in memory, traditionally at 0xFFFFFFFF. This location cannot be occupied by any other process local memory. To ensure data integrity, the CreateMutex API is used to create the mutex object. In addition, the waitformultipleobject API is used to handle the mutex events by enforcing a process waiting time. The waiting time for each process is dependent on releasing mutex events at the other process end.

After the HANDLE is created, IPC operates in a closed cycle where it asks the IC component to hold the mutex object and to write its inputs in the shared memory. When the mutex object is released, IPC asks Paramics plug-ins to hold the mutex object and read these inputs. Paramics then releases the mutex object and the IPC asks the IC component to write its inputs again in the shared memory, and so on until the end of the simulation experiment. Figure 4.3 summarizes this sequence of events.

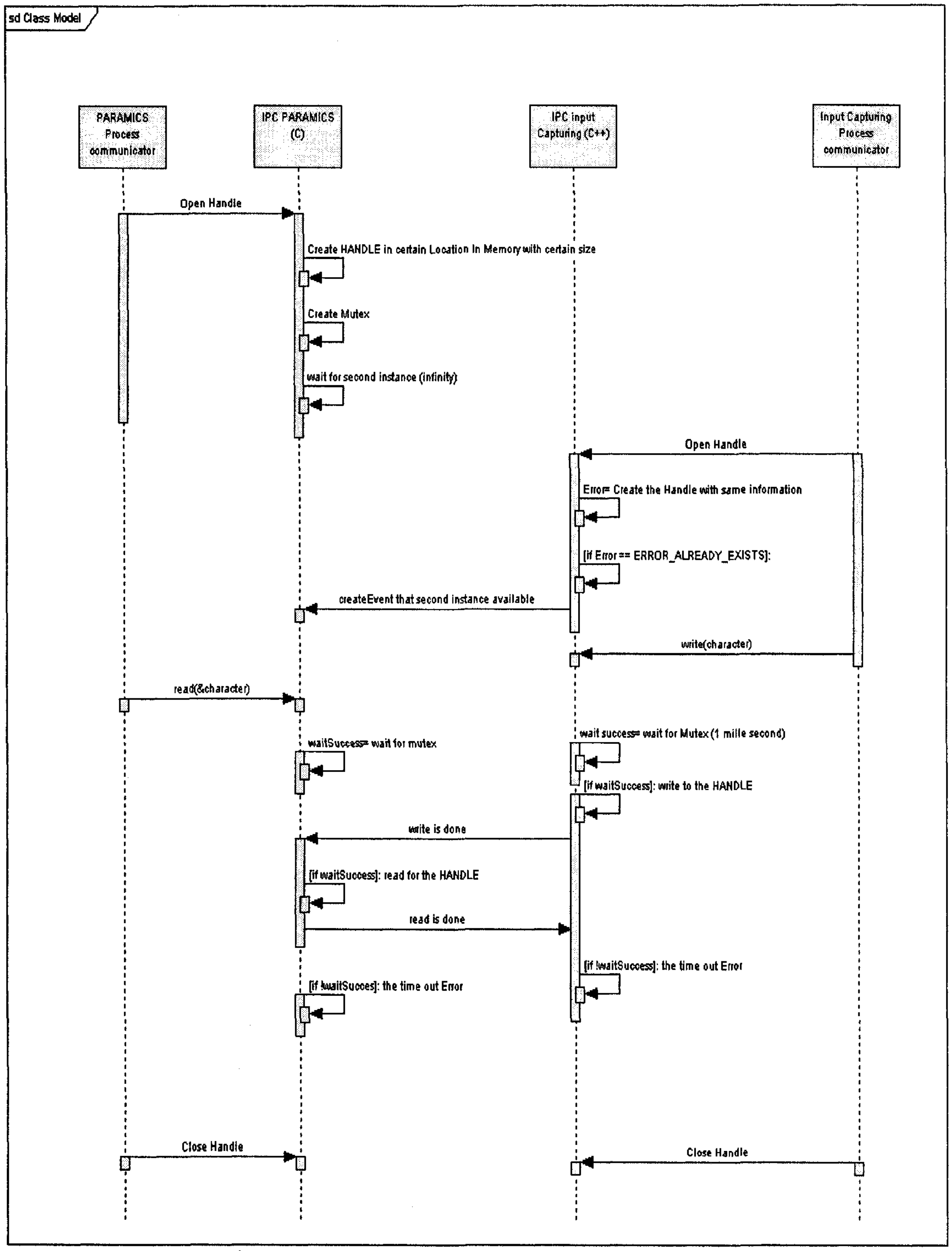


Figure 4.4 Shared Memory Sequence Diagram

4.8 MIXED REALITY SYSTEM CAPABILITIES AND LIMITATIONS FOR USE

In summary, the developed mixed reality system is a traffic analysis platform that is intended to enable credible evaluation of drivers' route choice behaviour within a controlled-lab setting. In such an environment, a human subject could be exposed to a pseudo-realistic driving experiment such as in a driving simulator but navigating through a real network such as a known city and surrounded by a realistic representation of actual traffic such as in microscopic simulation models. The developed platform offers the opportunity to monitor drivers' route choice decisions while maintaining control over external factors such as traffic conditions, disseminated information type and reliability. In conclusion, the mixed reality system capabilities (not including the microscopic traffic simulator capabilities) and limitations are:

Mixed Reality System Capabilities

- External control of the routing decisions of the test vehicle using a PC-input device: a steering wheel or a keyboard. This added feature allows a subject to navigate her/his vehicle in terms of routing decisions within a realistic traffic network.
- External control of the lane-changing manoeuvres of the test vehicle using a PC-input device: a steering wheel or a keyboard. Maintaining control over all lateral movements, including lane changing, enhance the realism of the simulated driving experience and hence contribute to the quality of collected data.
- User-defined information provision/guidance interface. Information type as well as reliability could be easily manipulated through the developed information provision interface.
- Monitoring and measurement of deliberation times and resulting choices. The platform allows the analyst to measure the time that the driver takes to make a route choice, measured from the instant the driver receives relevant information to the instant a decision is executed.

Mixed Reality System Limitations for use

- Longitudinal control of test vehicle, in terms of speed, acceleration/deceleration is internally performed by the car following model of the micro-simulator.
- All movements of surrounding traffic and congestion evolution are modelled and controlled by the micro-simulator.
- Interpretation of routing directions is referenced to a pre-specified default route: "default route benchmarking." As Paramics APIs have no access to the network geometry, a "do-nothing" input scenario within a decision zone is interpreted as a desire to continue on or unwillingness to divert from the current route. A "right/left" input is referenced from the default route exit. The display of the next exit number, prior to turning, precludes any possible misconception that might occur in this regard.

5 IN-LAB ROUTE CHOICE EXPERIMENTAL DESIGN AND SETUP

5.1 PRÉCIS

An experimental procedure is designed to collect route choice data in a laboratory setting. While the factors influencing drivers' routing decisions are numerous, an experimentation scope is defined for the intended analysis. A real-life traffic network in the heart of downtown Toronto is used as a test network. Manipulation of traffic conditions is performed to match variations in the real-life environment. Traffic information is communicated to test subjects through a Variable Message Sign (VMS). The mixed reality traffic analysis platform, presented in chapter 4, is used as the experimentation tool. Subjects are asked to navigate a vehicle through the microscopic reproduction of the test network while given various descriptive and prescriptive traffic information. Routing decisions and deliberation time frames are recorded. For complementary and comparative purposes, a more classical map-based point-and-click route choice experimental procedure is also used. Experimentation is conducted in three successive phases: an information/tutorial session, a learning session, and actual experimentation sessions. This chapter presents detailed description of the experimentation setup in terms of test network, experimental tools, sample size, and experimentation phases.

5.2 EXPERIMENTATION OVERVIEW

In-lab simulated route choice experiments are designed to monitor and record route choice behaviour data for analysis and calibration purposes. Subjects are asked to perform routing decisions in a simulated driving environment, under different information scenarios, while their reactions are monitored and recorded. Observed measures are to be used in the assessment of route choice behavioural patterns as well as in the estimation of DFT route choice model parameters. As such, the experimental setup is outlined to serve these purposes.

Drivers' route choice behaviour is influenced by many personal and situational factors. Socioeconomic, demographic, and personality-related attributes are all personal factors that impact route choice behaviour. On the other hand, the choice context (pre-trip vs. en-route), information-related characteristics (such as information dissemination technique, information timeliness, information form, and information reliability), time pressure, trip purpose, and weather conditions are all examples of situational factors that are expected to influence the route selection process.

Incorporation of all contributing factors in drivers' route choice behaviour within the experimental setup is unfeasible. However, some of the main factors are considered for investigation. In the following, the broad lines of the experimentation scope are highlighted. Further detailed discussions on some experimentation aspects are presented in subsequent sections of this chapter.

1. *Homogenous sample;* a homogenous sample of drivers of 30 participants is envisioned. Subjects' recruitment is mainly focused on graduate and undergraduate students at the University of Toronto, primarily because of their relative availability and willingness to spend long hours conducting the experiments. The sample is homogenous in terms of age, educational level, income level, and driving experience. Nonetheless, personality-related attributes are variable. An effort was made to make the sample size as large as feasible, given the time consuming nature of each test.
2. *Recurrent Trips;* recurrent trips represent the main trip type within a traffic network. Recurrent trips are those performed on a regular basis (such as work trips, and school trips.), and hence the network and typical traffic patterns are familiar to the driver. The focus of our analysis is limited to recurrent-type trips. The experimentation environment is set up to simulate a recurrent-type trip in three ways. First, subjects (students) are informed about the intended purpose of their simulated trip; a school trip. Second, a major traffic corridor leading to downtown Toronto (near the university campus) is adopted as the test network. Finally, although subjects are generally familiar with the city and this particular main corridor, they are further familiarized with the test network through a pre-experimentation learning session. Familiarity with the

network layout, traffic conditions and information provision characteristics are main components of recurrent-type trips.

3. *VMS Information Dissemination;* VMS display of traffic information is used throughout the route choice experiments. The effect of varying communication technologies (e.g. VMS vs. In-vehicle navigation device) on drivers' behaviour isn't addressed within our analysis scope. The test network has a VMS on the main corridor, and a similar setup was reproduced in the model.
4. *Two forms of information provision;* during the experimental trips, disseminated traffic information takes one of two forms: a descriptive and a prescriptive form. Descriptive information provides test subjects with reports on traffic conditions on alternative routes, using high-level description of congestion states. On the other hand, prescriptive information recommends the current fastest route to the test subject in an explicit manner. Both types of information are disseminated with varying levels of accuracy or reliability.
5. *Two information reliability levels;* drivers compliance to disseminated information is mostly based on their level of confidence in information content. Information reliability is, hence, a key feature in this context. Information reliability level represents the probability of disseminating correct information to drivers. While it is not feasible to test a wide spectrum of reliability levels within a limited sample size of participants, two pre-specified reliability levels are considered: 0.6 and 0.8 reliability levels.
6. *Non-obstructing weather conditions;* the effect of weather conditions on drivers' route choice behaviour is not considered within our experimental scope. Accordingly, no weather-related obstructions are perceived by test subjects.
7. *Steady-State perception of traffic conditions;* drivers update their perceptions of traffic conditions through day-to-day learning as well as day-specific learning. As the focus of our research scope is restricted to modelling the decision-making process and not the learning process, drivers are allowed to learn about the network, typical traffic conditions, and the reliability of

provided information if any. This day-to-day learning is achieved in the experimental setup through a large number of pre-experimentation learning trips. After the learning trips, drivers' familiarity with the test environment is assumed to have reached steady state. On the other hand, imposing restrictions on day-specific perceptions updates is more challenging. In an attempt to address this challenge, congestion levels on subsequent route segments are varied independently. As such, a congested route segment does not have any significant impact on the congestion level of subsequent segment. Subjects are informed about the independence of congestion levels of successive segments of the alternative routes. Furthermore, subjects are informed that disseminated information content is only relevant to the route segments of alternative routes beyond the upcoming decision node. No influence of current experienced traffic conditions is, accordingly, considered.

5.3 TEST NETWORK

5.3.1 Network Layout

The test network is part of the Gardiner/Lakeshore major corridor on the waterfront of downtown Toronto, eastbound from the Humber Bridge to Spadina Avenue, as shown in Figure 5.1. This is the main traffic corridor leading to downtown Toronto from the western suburbs. While the Gardiner is a high-speed freeway with limited access, Lakeshore is a parallel surface arterial with lower speed and a series of traffic lights. However, when the Gardiner is heavily used, Lakeshore can be an appealing alternative. For the selected test stretch, there is a transfer point from the Gardiner to Lakeshore and vice versa, offering drivers an opportunity to divert, if they so choose. The length of the test portion of the Gardiner Expressway is 8.340 km divided into 4.415 km, and 3.925 km, before and after the diversion point. The Lakeshore alternative, on the other hand, is 8.432 km, with the decision node at 5.208 km from its beginning.

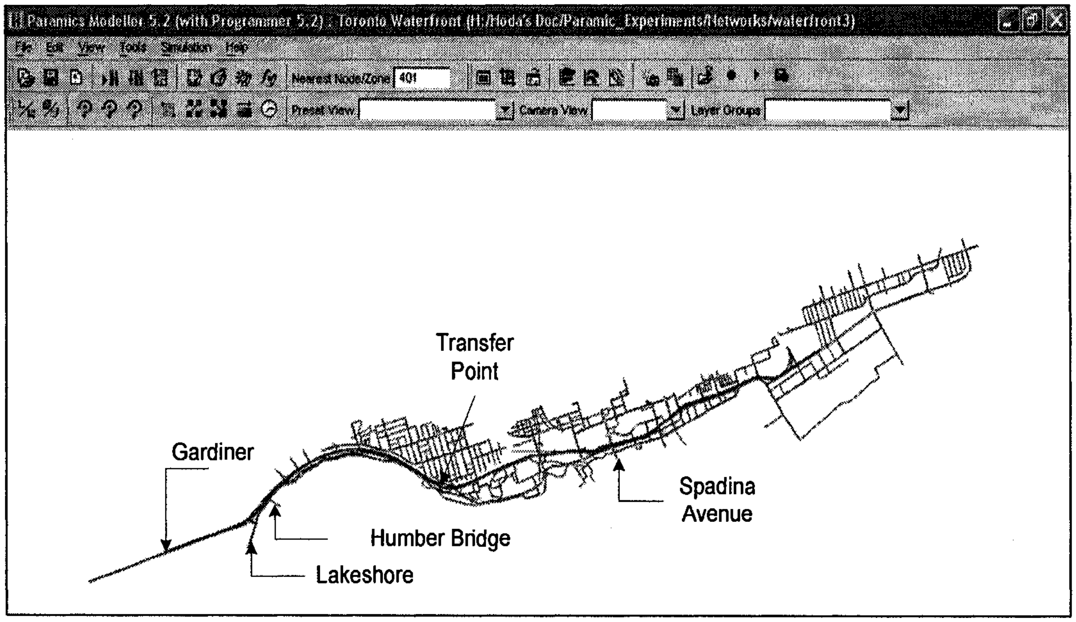


Figure 5.1 Test Network Layout

5.3.2 Experimental Traffic Patterns

Traffic conditions on alternative routes are stochastically controlled using pre-specified congestion probabilities. Each of the alternative routes is divided into two sections: before and after the divergence point. Each section can be in one of two possible congestion levels: congested or uncongested. While the uncongested level represents a free-flow traffic scenario, the congested one represents travel times at capacity, both with stochastic variations around a mean value. The adoption of such extreme traffic conditions is targeted to avoid misconceptions during the learning phase of the experiments. The learning phase, as will be discussed in detail in later sections, is targeted to formulate the subjects' perception about traffic patterns. More distinguishable congestion levels are easier/faster to grasp. In the following, the manipulation of congestion levels in terms of travel times and probabilities of occurrence is discussed in detail.

5.3.2.1 *Travel Times Setup*

A travel time distribution is defined for each route section, under each congestion level. Normal probability distributions are assumed. As such, a mean value and a Coefficient of Variation (CV) are specified for each route section, under each congestion level. The adoption of a travel time probability distribution is targeted to enhance the realism of the simulated experimental trips. It is unrealistic for a driver to encounter exactly the same travel experience on repeated trips. While the stochastic nature of micro-simulation runs would implicitly introduce some dispersion on experienced travel times, this dispersion is limited to minor traffic stream interactions. This limited effect could be insignificantly perceived by subjects. As such, the introduction of an externally imposed dispersion (through pre-specified CVs) is considered.

Mean values of the adopted travel time distributions are specified based on a classical Greenshields-type traffic flow model. However, traffic stream interactions, within each experimental trip, are captured and represented by the microscopic traffic simulator. Greenshield's traffic flow model assumes a linear speed-density relationship (Equation 5.1). Based on extensive micro-simulation runs of the test network, free flow travel times are identified for all route sections. The free-flow travel times are used as the uncongested mean travel times. On the other hand, the relationship between the free-flow speed (U_f) and the critical speed at capacity (U_o) (presented in Equation 5.2) is used to define the congested mean travel times. Accordingly, the mean values of the congested travel times are set to be twice the free flow values. Table 5.1 presents the adopted values, for all route sections.

$$U= U_f-(U_f/K_j)K \tag{5.1}$$

$$U_o=U_f/2 \tag{5.2}$$

Where:

- U; speed (km/hr)
- U_f; free-flow speed
- K; density (veh/km)
- K_j; jam density
- U_o; speed at capacity

Table 5.1 Test Network Mean Travel Times

Congestion Level	Gardiner Mean TT (mins)		Lakeshore Mean TT (mins)	
	Sec 1	Sec 2	Sec 1	Sec 2
Congested	6.2	5.8	8.5	7.5
Uncongested	3.5	3.1	4.5	3.5

Travel time distribution CVs are realized through the definition of three dispersion degrees; a high, a medium, and a low degree. Allocation of a dispersion degree to a route section is based on its type as well as its congestion level. While congested freeway sections are considered the highest with respect to travel time dispersion degrees, uncongested freeway sections are expected to be the lowest in this regard. As such, either a high or a low dispersion degree is considered for the Gardiner route sections, based on trip-specific congestion levels. As for the surface street alternative, traffic signals are expected to contribute the most to travel time variations, decreasing the impact of congestion-induced variations. Accordingly, as a reasonable simplification, a medium dispersion degree is considered for both sections of Lakeshore, under both congestion levels.

Specification of a CV value for each dispersion degree is performed on the basis of minimizing the overlap between travel time distributions of different congestion levels, for each route section. The more the overlap, the more difficult it is to identify different congestion levels, in the learning phase. A minimal overlap is targeted to facilitate the learning phase and to ensure correct perceptions of traffic patterns. Table 5.2 presents the selected CVs for each route section, under each congestion level.

Table 5.2 Test Network Travel Time Distributions Coefficients of Variations

Congestion Level	Gardiner CV (%)		Lakeshore CV (%)	
	Sec 1	Sec 2	Sec 1	Sec 2
Congested	5	5	2	2
Uncongested	1	1	2	2

5.3.2.2 Congestion Level Probabilities

In each experimental trip, traffic is generated according to trip-specific congestion levels. Four congestion levels need to be defined prior to starting each experimental trip; 2 routes with two sections per route. Trip-specific congestion levels are stochastically generated based on pre-specified probabilities. Congestion level probabilities are selected on the basis of maintaining the real-life competitiveness frame between the two alternative routes. Table 5.3 presents the chosen probabilities.

Table 5.3 Test Network Congestion Levels Probabilities

Congestion Level	Gardiner		Lakeshore	
	Sec 1	Sec 2	Sec 1	Sec 2
Congested	0.6	0.6	0.4	0.4
Uncongested	0.4	0.4	0.6	0.6

5.3.3 Information Provision

The assessment of the impacts of traffic information characteristics on drivers' route choice attitudes is one of the main objectives motivating the undertaken experimental analysis. Two information related attributes are addressed within our experimental scope: information form and information reliability. A VMS information-dissemination technology is adopted throughout the experimental analysis. In a simulated trip, two routing decisions are to be made: a pre-trip decision on where to start the trip and an en-route decision on whether to divert or not. For pre-trip decisions, information is displayed on screen, at the beginning of each experimental trip. En-route information is presented in the form of a text message that appears beside the driven vehicle on the visual display of the simulated experimental trip. En-route information is disseminated at approximately 1100 m from the decision node (based on the guidelines provided by the Ministry of Transportation of Ontario, Canada, for operations of changeable message signs)

With respect to information type, information is disseminated to subjects in two forms: a descriptive and a prescriptive form. In the following a detailed description of the content of each information form, for each routing decision, is presented:

1. No information; subjects are not provided with any source of traveller information.
2. Descriptive information; subjects are provided with expected congestion levels on each of the alternative route sections in the form of "route x, section i, is moving well/slow." In pre-trip choice situations, information content covers both sections of both routes. En-route information content considers only the second half of each route (beyond the divergence point).
3. Prescriptive information; a specific advice to take the faster route is displayed to the driver, in the form of "Take the Gardiner" or "Take Lakeshore." The recommendation is based on the comparison between travel times of available alternative routes. In pre-trip choice situations, the disseminated advice is based on whole-route travel times. However, travel times of the second portion of the trip are only considered in the en-route context.

Current real life applications of ATIS are mostly based on instantaneous rather than predicted traffic conditions. As such, by the time drivers pass through a given route segment, the previously provided information might no longer be valid. The collective responses of other drivers to disseminated information could significantly alter evolving traffic patterns. Information reliability can also be affected by numerous other factors such as surveillance (detection) method, communication lag and other. Even predicted information, if available, can be inaccurate and dependant on the prediction method. Therefore, information reliability, or lack of, is always a concern. The assessment of the impact of various levels of information reliability on route choice behaviour is, hence, investigated. Reliability levels, within our analysis, refer to the probability of providing correct information to drivers. Accordingly, disseminated information content during an experimental trip is not always correct, but rather stochastically reliable based on pre-specified reliability levels. It is important to highlight that the information reliability level is fixed for each subject throughout her/his experimental trips.

While reliability levels may vary, theoretically, from 0 to 1, only two levels are considered, for practicality and due to the limited sample size of participants. The chosen levels are intended to be on the reliable side (above 0.5) for the information to be of some utility. As such, subjects are divided into two groups, as follows:

- *Group 1;* with an information reliability level of 0.6
- *Group 2;* with an information reliability level of 0.8

5.4 EXPERIMENTAL TOOLS

Two sets of route choice experiments are designed, using the same network but with two different methods or tools. The first method is a map-based one, where subjects perform their routing decisions for an imaginary trip on a computer screen with map view of the test network using mouse clicks. The second procedure is an application of the mixed reality system, where subjects navigate their vehicles through a microscopic simulation model of a real traffic network and actually experience the consequences of their decisions, possibly getting stuck in severe and lengthy congestion. If the driver chooses a badly congested route, she/he will be behind the steering wheel for a long time until congestion clears, the same way as in real life.

The reason for varying the testing procedure is two fold. The first objective is to obtain a reasonably large sample size within the limited feasible experimentation time frame. While mixed reality testing procedure has the advantage of more realistically reproducing the choice environment, it is challenging in terms of time consumption. Real-time simulations of a fairly large number of experimental trips are time demanding. As such, a point-and-click map-based testing procedure is also used to augment the sample size. The map-based testing procedure is restricted, though, to pre-trip routing decisions. The rationale is based on the intuitively lower value of reproducing the details of the choice environment in pre-trip route choice contexts.

Another objective for varying the testing method is to compare and evaluate the impact of each method on the quality of experimental results. The main question is: *does the virtual reproduction of the choice environment in the mixed reality simulator improve over crudely asking the user to state her/his choice using a map?* A comparative analysis between data generated using both testing procedures is conducted to answer this question. Details of both experimental procedures are discussed in the following sections.

5.4.1 Map-based Method

The map-based experimental procedure adopts a traditional macroscopic level framework. An interactive Windows-based computer program is developed for this purpose. Each trip starts with a map display of the test network and trip-specific information. Figure 5.2 displays a screen shot of a map-based experimental trip. Information type is randomly generated for each trip. Information content is stochastically reliable. Subjects are asked to perform pre-trip route choices for the imaginary trip starting from the Humber Bridge to Spadina Avenue given the displayed information. Choices are in the form of a mouse click on a tab with the chosen route name. The chosen route as well as the Deliberation Time (DT) is recorded for each trip. The deliberation time is recorded starting from the display of a trip-specific information scenario until a choice is made (a mouse click). At the end of each trip, a feedback window displaying trip travel time and travel distance appears on screen. The displayed travel time is stochastically generated given congestion level probabilities and travel time distributions.

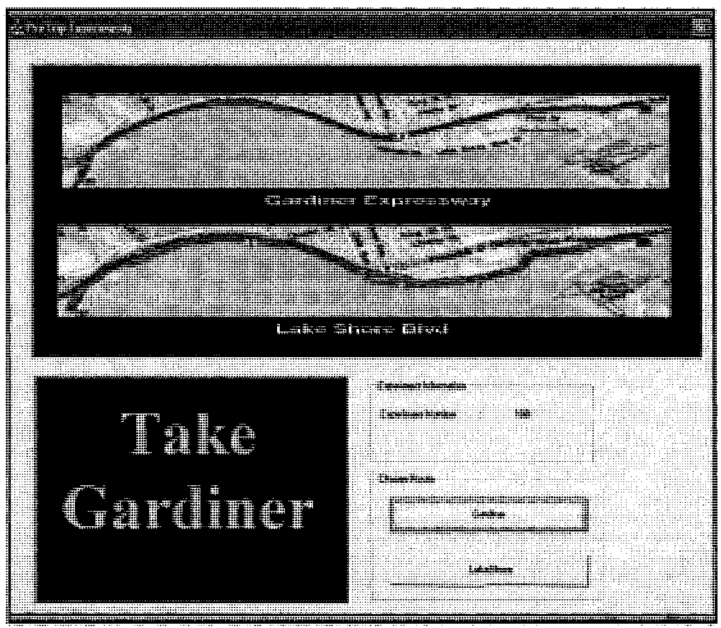


Figure 5.2 Map-based Experiment Interface

5.4.2 Mixed Reality Experimental Method

In a microscopic simulation model of the Gardiner/Lakeshore corridor, test subjects are asked to drive their vehicles eastbound from the Humber Bridge to Spadina Avenue, using the developed mixed reality platform (discussed in detail in chapter 4). The microscopic reproduction of the test network is provided by the Toronto ITS Centre. The model is only part of a full scale microscopic model of the waterfront area in downtown Toronto, developed by former researchers at the Toronto ITS Centre.

Prior to starting the simulation, subjects are required to specify a pre-trip route choice under the "no information" scenario. This pre-trip choice is used by the mixed reality system as the driver's default route. Using the steering wheel, subjects navigate the driven vehicle through the test network and throughout the simulated trip. Figure 5.3 shows a snapshot of the mixed reality simulator-driver interface, with a circle superimposed on the subject vehicle. At approximately 1100 m from the diversion point, subjects receive information with a random type (descriptive or prescriptive) and a stochastically reliable content. To enhance the realism of the simulated experiment, the microscopic simulation is adjusted to be visualized in real time; where a simulated minute of traffic takes an actual clock minute. Accordingly, the experiment duration is actually the trip travel time which can range from 6 to 16 minutes.

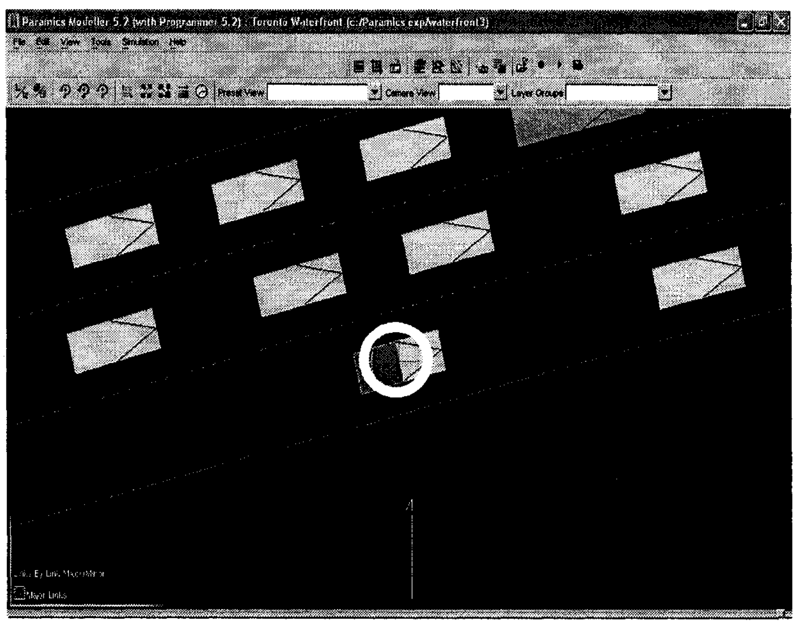


Figure 5.3 Mixed-Reality Simulator-driver Interface

The variation of different congestion levels within the microscopic traffic simulator is achieved through the development of a traffic control API Plug-in. The main task of the developed plug-in is to stochastically generate trip-specific traffic conditions. As mentioned previously, a congestion level is defined for each route section based on pre-specified congestion probabilities. Generating trip-specific congestion levels is discussed in the following:

- _Uncongested Levels;_ represent the basic traffic conditions scenario. Default low demand levels are pre-specified to allow for a free-flow travel environment. The stochastic nature of the microscopic simulation model induces the required limited dispersion (low and medium degrees) in trip-travel times. To maintain control over experimental traffic conditions, routing of the background traffic is pre-defined. As such, surrounding vehicles are not allowed to divert from one route to the other, but rather, forced to stick to their pre-defined routes.
- _Congested Levels;_ an incident is introduced at a certain time/location of the congested route section. The incident is designed to fully block the road segment for a few minutes. The incident duration is adjusted to fit the pre-specified travel time probability distributions of congested route sections. OD demands are slightly adjusted to ensure the independence of traffic conditions of successive route segments. The main objective of the OD demand adjustments is to avoid traffic spill-over from congested route segments to uncongested ones. Similar to the uncongested levels, routing of the background traffic is fixed to a pre-defined scenario to preserve trip-specific traffic conditions.

A data set of pre-trip/en-route choice decisions and deliberation times is recorded for each simulated trip. While the identification of routing decisions is performed through the continuous monitoring of the driven vehicle's current link, the deliberation time identification is more challenging. Subjects are asked to start their deliberation process once the disseminated information is displayed on screen. Subjects are also asked to press a decision button on the steering wheel, once they reach a decision. The time elapsed from the information display until the press of the decision button is recorded by the system as the deliberation time.

5.5 Experimentation Sample Size

As mentioned previously, the purpose of the intended experimental analysis is two fold. First, observed data are to be used for the assessment of route choice behavioural patterns, under both testing procedures (independently and comparatively). Second, observed choice measures are to be used in the estimation of the DFT route choice model parameters. As such, subjects are introduced to different information scenarios, while their choice measures (chosen option, and DT) are recorded. Due to the probabilistic nature of the decision-making process, aggregate choice measures for each subject are estimated from identical choice situations. Choice percentages and Mean Deliberation Times (MDTs), under each information scenario, are the experimental observed measures. Obviously, the more the number of experimental trips per information scenario, the more representative the observed measures are. Nonetheless, a feasible sample size needs to be defined.

Specification of a reasonable number of experimental trips per information scenario is based on sensitivity analysis. A simulation-based sensitivity analysis is performed on the dispersion of aggregate choice measures (choice percentages and MDTs) with respect to different numbers of repeated deliberation experiments. The simulation of the base-case deliberation process is conducted based on the DFT route choice conceptual model, using assumed parameter values. Under each considered number of repeated deliberations, choice percentages and MDTs are estimated repetitively (50 independent times). A CV is then estimated for each observed measure under each number of repeated deliberations. Figure 5.4 presents the sensitivity-analysis results.

A significant decrease in estimated CVs is noticeable around 10 repeated deliberations. The decrease continues till it reaches a minimal level at 10 000 repeated deliberations. A reasonable range is identified between 10 and 50 repeated deliberations. Specification of an appropriate number of experimental trips per information scenario, within this range, is dependent on experimentation time frame limitations. While a map-based experimental trip takes a couple of seconds to perform, a mixed reality-based trip is time-demanding. Each simulated experimental trip takes from 6 to 16 minutes to complete, depending on trip-specific circumstances. As such, a higher number of map-based experimental trips is considered.

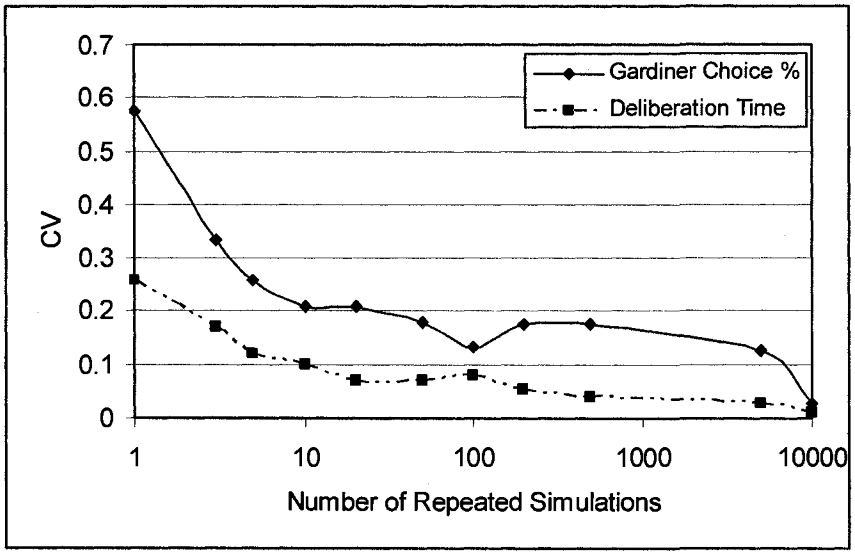


Figure 5.4 Sensitivity of Aggregated Choice measures to the number of deliberation repetitions

Accordingly, each subject is asked to perform a set of 400 map-based trips divided as follows:

- 10% under no information
- 25% under prescriptive information, with stochastically reliable content, based on trip-specific traffic conditions and information reliability level.
- 65% under descriptive information, with stochastically reliable content, based on trip-specific traffic conditions and information reliability.

As for the mixed reality experimental trips, a limited number of 40 trips per subject is conducted. Each trip is composed of a pre-trip decision under the "no-information" scenario and an en-route decision with either a descriptive or a prescriptive information form, on a random basis. The content of disseminated information is based on trip-specific traffic conditions and information reliability.

5.6 A WALK-THROUGH THE EXPERIMENTATION PHASES

5.6.1 Information Session

The information session is a tutorial and information exchange session, between the experimenter and test subjects. The experimenter provides test subjects with a brief overview of the purpose of the intended experimental analysis. Information related to the experimental scope, setup, and tools are communicated to test subjects. On the other hand, subjects are asked to communicate some relevant personal information through a pre-experimentation questionnaire (a copy of the questionnaire is provided in appendix A). The questionnaire is divided into the following four sections:

- *Section 1: Socio-economic/Demographic Attributes*. Collects subject's age, gender, occupation, education level and income level.
- *Section 2: Personality Attributes.* Collects subject's attitudes toward adventure and discovery through a test of 6 simple questions. The adopted test is the same test used in a survey of route choice behaviour conducted by Khattak *et al.* (1995). A risk index is estimated for each subject, based on a scoring system. Alternative answers for each question are given a score from 0 to 4 in an ascending order; starting with 0 for option (i). The risk index, for each subject, is estimated to be the sum of scores of all 6 questions. High risk index indicates a risk-seeking type of personality.
- *Section 3: Route Choice Attributes.* Collects subject's perceptions of the significance of the three considered attributes (travel time, distance, and freeway usage) as criteria for routing decisions.
- *Section 4: Driving Experiences.* Collects information regarding real-life driving experiences in terms of years of experience, familiarity with VMS information dissemination and real-life familiarity with the test network.

5.6.2 Learning Session

After completing the information session, a learning session is mandatory with two objectives: a) getting subjects familiar with the experimental setup and b) formulating their perception of travel times, congestion levels and information reliability for the test network. For the first objective, subjects are introduced to the map-based and the mixed- reality experimental procedures. A number of trial trips, at the subject's request, are conducted using both testing procedures. Subjects are asked to take as much time as they want to familiarize themselves with both testing tools.

For the second objective, a set of 150 learning trips are conducted. The first 100 learning trips are designed to enable the subject to form a clear perception of traffic patterns. As such, subjects are not provided with any source of traveller information during those trips. Afterwards, 50 learning trips with randomly varying information type and stochastically reliable content are designed to familiarize subjects with information accuracy levels. To speed up the experimentation process, the 150 learning experiments are conducted using the map-based procedure with a feedback of travel time for each performed trip. However, subjects are informed that traffic patterns and information characteristics are identical for both testing procedures and that the use of the map-based procedure is only for expediency and convenience purposes. Conducting 150 learning experiments using the mixed reality simulator would have been unrealistically time consuming and tiring for the subjects and was hence ruled out as an option.

5.6.3 Actual Experimentation Sessions

A number of sessions are scheduled for conducting actual experimental trips using both testing procedures. The first session is devoted to the map-based testing procedure, where each subject is asked to perform a set of 400 map-based experimental trips. A second series of sessions is devoted to the mixed reality experiments. A set of 40 mixed reality trips are to be conducted. Test subjects are asked to budget approximately 10 hours for the mixed reality experiments, possibly spanned over a number of sessions as desired. Prior to starting this phase of the experimentation, subjects are reminded of the scope and seriousness of the intended experimental analysis.

6 ANALYSIS OF EXPERIMENTAL ROUTE CHOICE BEHAVIOURAL PATTERNS

6.1 PRÉCIS

The developed experimental platforms and setup are used to monitor and record drivers' route choice behaviour under varying conditions. Subjects are recruited to perform the designed laboratory route choice experiments. Two sets of experiments are performed by each subject. The first set of experiments is performed on an interactive map-based route choice simulator that allows subjects to choose one of the routes displayed on a map without actually having to drive the routes. The second set of experiments is performed on the developed mixed reality platform which allows for a more realistic choice environment and directly exposes drives to the consequences of their decisions. The collected experimental data serve two purposes; to analyse and assess patterns in route choice behaviour, and to calibrate the DFT route choice model. This chapter is devoted to identifying and analyzing route choice behavioural trends for both sets of experiments, independently as well as comparatively. The scope of the independent analysis is limited to the assessment of the impact of a set of key situational and personal factors on subjects' pre-trip and en-route choice behaviour. A comparative analysis is then devoted to the assessment of the potential of each testing method as a route choice data collection tool. Finally, a summary of concluding remarks on main findings is presented.

6.2 PARTICIPATION IN LABORATORY EXPERIMENTS

Students are recruited at the University of Toronto to perform the laboratory experiments. Experimentation is conducted in the ITS center and test-bed at the University of Toronto. As a participation incentive, a compensatory gift of $75 is granted upon completion of the roughly 10 hours of experiments. Participants are graduate and undergraduate students in the Department of Civil Engineering. The total number of participants is 30. All participants have prior driving experience.

An overview of the profiles of participating subjects, based on the questionnaire results, is presented in the following;

1. Socioeconomic/Demographic Profiles
    - Age group, 20-30 years old
    - Gender split, 22 males and 8 females
    - Occupation, 14 undergraduate students and 16 graduate students
    - Annual income level, all below $40,000, with 60% below $20,000

2. Personality Profiles

Based on the scoring system discussed in section 5.6.1, a risk index is estimated for each subject. Estimated values range from 10 to 22. Figure 6.1 summarizes the frequency distribution of risk scores in the sample.

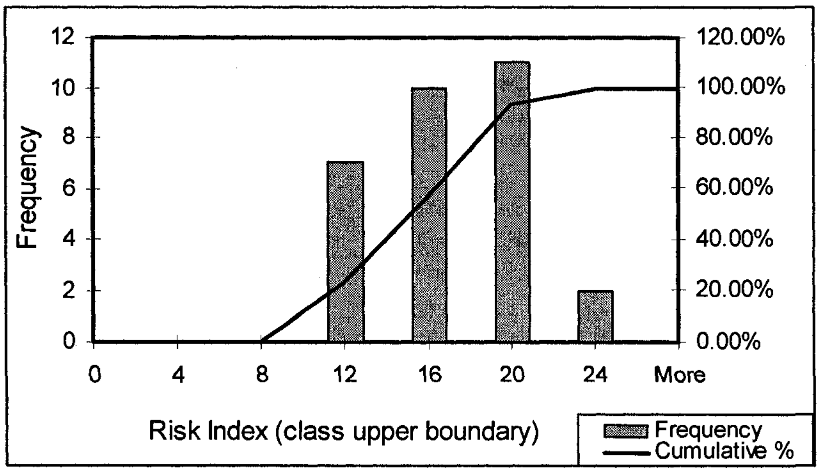


Figure 6.1 Participant questionnaire-based risk-index frequency distribution

3. Route Choice Preference Attributes
    - The importance of each of the choice attributes (travel time, distance, and freeway usage) varies from one person to another. Subjects were asked how frequently they consider each of the attributes in their decision making. Figure 6.2 summarizes subjects' frequency distributions for each of the three attributes.

- As expected, travel time is observed to be the most saliently considered attribute in route choice decision-making processes. While travel time is incorporated as a decision attribute by all participants, it is never considered solely.
- Freeway usage and travel distance seem to be relatively less important compared to travel time.
- While all drivers perceive an increase in travel time or distance to be on the negative side, freeway usage perception varies across drivers. Some drivers intuitively prefer taking a freeway, while others prefer the surface street. Based on the questionnaire results, a preference for using freeways is stated by 67% of the participants. A preference to using the surface street is stated by 16% of participants. The remaining 16% are neutral.

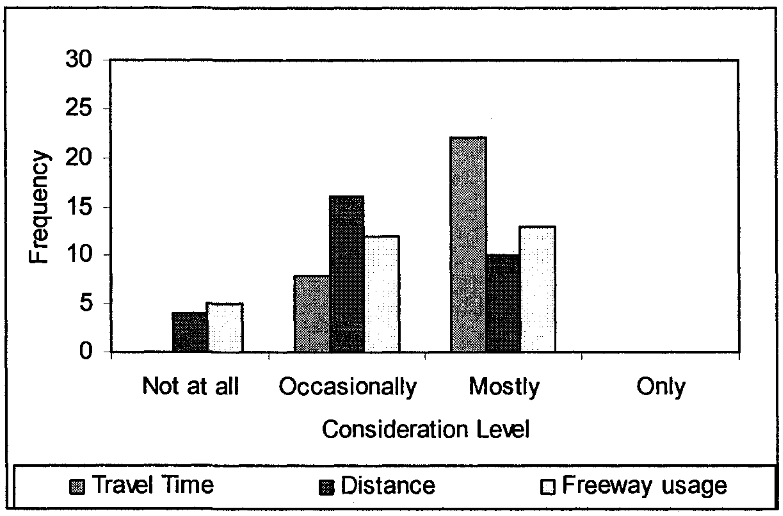


Figure 6.2 Participants' stated levels of consideration of route choice attributes

4. Driving experience
   - All participants have prior driving experience of less than 10 years. The number of experienced years varies as follows:
     i. 36% have less than 2-year experience
     ii. 30% have driving experience between 2 and 5 years
     iii. 33% have more than 5 years of driving experience.

- Most participants are familiar with VMSs as an information dissemination technology (87%).
- Only 50% of the participants previously drove on the real-life version of the tested routes.

6.3 MAP-BASED PRE-TRIP EXPERIMENTAL ANALYSIS

Map-based experiments are concerned with pre-trip decisions only. Subjects are asked to perform pre-trip route choice decisions for the imaginary trip along the Gardiner/Lakeshore corridor of downtown Toronto, starting from the Humber Bridge to Spadina Avenue, given the displayed information. The chosen route as well as the deliberation time is recorded for each trip.

6.3.1 Preliminary Data Filtering

The recorded data inevitably contain noise and outliers due to possible distraction of the test subjects during some experiments. The first step in the analysis is therefore to identify and remove possible outliers to avoid skewing the analysis. The credibility of the data recorded from a simulated trip is assessed based on the time taken to make a decision. In the map-based procedure, the recorded deliberation time is simply the time elapsed from the display of an information scenario until the subject makes a choice by clicking on the chosen-route tab. Excessively long time frames are attributed to possible loss of focus or possible external distractions. Data from such trips are disqualified and removed from further analysis. For this purpose, an outlier analysis is performed with respect to deliberation time, for each subject *independently*. Trips with deliberation times within 3σ from the subject's mean deliberation time (MDT) value are considered credible. Values outside this boundary are extracted as outliers.

Qualified results of the map-based experimental procedure for each subject are grouped under 12 information scenarios (with respect to form and content). Table 6.1 summarizes the categorization of information scenarios. For each subject, under each scenario, Gardiner-choice percentage (the number of trips where the Gardiner is chosen relative to the total number of trips, %G) and MDT are calculated. Under the scenario column in Table 6.1, each scenario is assigned an abbreviated "name" to be used in the rest of the analysis. All descriptive information scenario names start with the letter D (for descriptive) followed by an indication of the congestion level on the Gardiner and an indication of the congestion level on Lakeshore. Prescriptive scenario names start with P, followed by an indication of which route was recommended.

Table 6.1 Map-based Experiment, Pre-Trip Information Scenario Categorization

Information Type	**Information Content**						**Scenario Abbreviation**
	Disseminated Section-based Congestion States [a]				**Combined Route-Based Congestion States** [b]		
	Gardiner		**Lakeshore**				
	Sec 1	**Sec 2**	**Sec 1**	**Sec 2**	**Gardiner**	**Lakeshore**	
Descriptive information	H	H	H	H	H	H	DHH
	H	H	H	L	H	M	DHM
	H	H	L	H			
	H	H	L	L	H	L	DHL
	H	L	H	H			
	L	H	H	H	M	H	DMH
	H	L	H	L			
	H	L	L	H			
	L	H	H	L			
	L	H	L	H	M	M	DMM
	H	L	L	L			
	L	H	L	L	M	L	DML
	L	L	H	H	L	H	DLH
	L	L	H	L			
	L	L	L	H	L	M	DLM
	L	L	L	L	L	L	DLL
Prescriptive information	Take Gardiner						PG
	Take Lakeshore						PLS
No information	Drive Safely						No-info

[a] H denotes a high travel time (congested), L denotes a low travel time (uncongested)
[b] M denotes a combined medium congestion level (for an entire route), resulting from the combination of a congested section and an un-congested one.

6.3.2 Decision-Factor Analysis

Drivers' route choices are outcomes of a decision-making process. This process itself stems from the interaction between personal profiles and situational factors. The scope of our factor analysis is focused on key personal/situational factors. Based on the experimental setup, three information-related situational factors are varied through the map-based testing procedure, namely: information form, information content and information reliability level. As such, the impacts of these three factors on the decision process are investigated. On the other hand, although the sample of subjects in this study is homogeneous in terms of many personal attributes such as age, income etc., key personal attributes of interest vary. In particular, the impacts of gender and risk attitudes on route choice behaviour are analyzed.

The analysis of the level of influence of each factor is performed in two steps. First, general behavioural observations are drawn from the aggregate measures of the investigated factors. Afterwards, the statistical significance of these observations is assessed through a set of Analysis of Variances (ANOVA) tests. All conducted ANOVA tests are performed under a 95% confidence interval, unless stated otherwise. ANOVA assumptions are maintained within the conducted analysis. A basic introduction to ANOVA and a summary of the complete ANOVA testing results are presented in appendix B.

6.3.2.1 Information Impact

Data from the map-based experimental procedure are reduced to two measures per scenario for each subject; %G and MDT. The calculated measures are then grouped with respect to the reliability of disseminated information (group 1 with 0.6 reliability levels, and group 2 with 0.8 reliability). The mean of the choice percentages and deliberation times for each group of participants under each information scenario is presented in Table 6.2.

Table 6.2 Map-based Experiment, Mean Observed Route Choice Measures Categorized by Information Reliability Level

Information Scenario	Group 1 (0.6 reliability)		Group 2 (0.8 reliability)	
	%G	MDT (sec)	%G	MDT (sec)
No-info	88.3	1.5	88.4	1.5
PG	92.8	1.5	95.0	1.3
PLS	57.3	1.8	30.9	1.7
DHH	89.1	2.1	85.2	2.0
DHM	53.0	2.2	31.3	2.2
DHL	33.6	2.0	16.2	2.0
DMH	88.2	2.3	87.5	2.1
DMM	86.8	2.4	85.1	2.1
DML	48.6	2.3	28.9	2.1
DLH	95.4	1.9	96.5	1.7
DLM	92.0	1.8	95.7	1.6
DLL	84.3	1.7	88.4	1.6

Preliminary Observations:

- Subjects tend to have an intuitive preference to take the Gardiner Expressway. This is reflected in the high choice percentage of the Gardiner under the No-info scenario (88%). This result reinforces and quantifies the notion that freeways are generally preferred to parallel surface streets.
- The stochastic nature of the decision-making process is manifested as a change in preferences is depicted between experimental trips, under the No-info scenario. While subjects' were more inclined to use the Gardiner (in about 88% of the trips), they choose Lakeshore on an occasional basis. This result challenges the assumption, underlying some route choice models (for example see Lotan, T. and Koutsopoulos, 1999), of a blindly default type of route choice behaviour, under normal conditions, in the absence of information.
- Gardiner choice percentages vary across scenarios. This means that subjects change preference, with various levels, under different information scenarios.
- A positive impact of information provision is generally observed, for both reliability groups. This indicates that drivers make use of the provided

information to augment their typical choice tendencies, in both cases when the information supports or oppose their default tendencies (under no information). Gardiner choice percentages increase above the base-line value (no-info scenario value) when the provided information substantially supports taking the Gardiner (PG, DLH, and DLM). A decrease in Gardiner choice percentages is also noticeable in information scenarios that support taking the Lakeshore alternative (PLS, DML, DHL), and thereby challenge or oppose subjects' intuitive preference.

- DHM, on the other hand, seems to be perceived as a neutral information scenario in the sense that perceived travel times are equal for both routes. A decrease in Gardiner choice percentage to somewhere in the middle-third percentage (30-60%) is observed for this scenario.
- While the rest of the information scenarios support taking the Gardiner (DHH, DMH, DMM, DLL), travel time gains aren't significantly considerable. Choice percentages for these scenarios are in the vicinity of the "no-information" scenario.
- Even though the variation in the reliability level between group 1 and 2 is not substantial (20%), the level of information reliability seem to alter the influence on behaviour and compliance.
- MDT varies, to various extents, across information scenarios. Deliberation times seem to be generally longer when any information is provided that needs to be mentally processed and acted upon. Deliberation times also seem to be generally longer when the choice is less obvious, for instance when both routes are congested (DHH).

Statistical Significance

With the above general preliminary observations in mind, a set of ANOVA tests are conducted to examine the statistical significance and gain meaningful insights from the experimental results. The main objective of these tests is to estimate the significance of information scenarios and information reliability in influencing subjects' route choice behaviour. The first set of tests is performed with respect to Gardiner choice percentages

(Lakeshore choice percentage is simply the remainder of 100%). A two-way ANOVA (with replications) test is conducted on choice percentages under the 12 information scenarios for the 2 levels of information reliability. Results of this test indicate the significance of information scenarios as well as the reliability level in altering choice percentages. However, no interaction is reported. In another words, disseminated information has a direct influence on choice percentages with different levels for different reliability groups. Yet, the impact direction is similar for both reliability groups.

To identify the significance of each information scenario independently, choice percentages of each information scenario are compared to the No-info scenario for each group of participants. Out of the 11 information scenarios, 4 scenarios significantly influences subjects' choice behaviour; PLS, DHL, DML, and DHM. The 4 scenarios challenge subjects' intuitive preference to take the Gardiner either by supporting taking Lakeshore (first 3 scenarios) or by indicating that they both have similar travel times (4th scenario). This indicates that the influence of information scenario is only significant when the displayed information is quite different than expected. Similar results are estimated for both information reliability groups, with different confidence levels (all more than 95%). As expected, as information reliability increases, the confidence level increases. The apparent route choice behavioural trend coincides with literature stating that drivers make their decisions based on conflict arousal resulting from unexpected changes in the environment that conflict with their prior experiences and expectations (Adler et al., 1993).

The second set of ANOVA tests are performed with respect to MDT. Results of the 2-way ANOVA test (for the 2 groups under the 12 information scenarios) indicate the significance of information scenarios in varying deliberation time frames. However, the impact of reliability level on MDT is less evident (significant only under 87% confidence interval), and no interaction is reported.

To gain further insight into the impact of information scenarios on MDT, each information scenario is compared to the no information case. Six out of 11 information scenarios have significant impact on MDT; DHH, DHM, DHL, DMH, DMM, DML. The six scenarios are descriptive ones reflecting a tendency of a more demanding decision-making process when disseminated information does not involve specific guidance. Five of the six information scenarios (DHH, DHM, DMH, DMM, and DML) represent a tight choice situation, where significant travel time gains are not readily perceived, and hence requiring longer decision time. In the remaining scenario (DHL), although the alternatives are clearly distinct, the information content substantially challenges or contradicts the subjects' intuitive preference to take the Gardiner, also resulting in longer deliberation times.

6.3.2.2 Gender Impact

The second dimension in this investigation is concerned with the assessment of gender differences in route choice trends. For this purpose, measures for each subject are clustered by gender. For choice percentages, data clustering is performed within each reliability group independently, due to the significant impact of information reliability on choice percentages. On the other hand, as the significance of information reliability in MDT is less evident, gender classification of MDT is performed on the entire data set. Tables 6.3 and 6.4 present the choice percentages and MDT for each of the clusters, under each information scenario.

Table 6.3 Map-based Experiment, %G categorized by Gender and Reliability Level

Information Scenario	**Group 1 (0.6 reliability)**		**Group 2 (0.8 reliability)**	
	Males	**Females**	**Males**	**Females**
No-info	88.3	88.3	93.9	77.5
PG	98.7	69.3	92.8	99.4
PLS	57.7	55.8	36.4	19.9
DHH	92.1	77.2	86.9	81.7
DHM	50.1	64.5	38.0	18.1
DHL	33.4	34.5	18.5	11.7
DMH	89.1	84.6	86.5	89.4
DMM	91.2	69.2	87.6	80.0
DML	46.4	57.7	33.0	20.6
DLH	97.7	86.5	95.3	98.7
DLM	96.4	74.4	94.3	98.6
DLL	88.0	69.4	90.0	85.3

Table 6.4 Map-based Experiment, MDT (sec) categorized by Gender

Information Scenario	Mean MDT (sec)	
	Males	Females
No-info	1.5	1.5
PG	1.4	1.6
PLS	1.7	1.9
DHH	2.1	2.0
DHM	2.1	2.6
DHL	1.9	2.4
DMH	2.0	2.8
DMM	2.1	2.7
DML	2.0	2.8
DLH	1.7	2.1
DLM	1.5	2.2
DLL	1.6	1.8

Preliminary Observations:

- Under lower reliability level (group 1), disseminated information tends to have a stronger positive influence on choice percentages for males. This is the case for both supporting and opposing information scenarios. A considerable increase in the Gardiner choice percentage is observed for PG, DLH, and DLM, while a decrease is observed for PLS, DML, and DHL. A different trend of information influence is observed for female participants. While a positive influence on choice percentages is observed in challenging information scenarios (PLS, DHL), supporting information scenarios induce a negative impact that is not readily explainable. The negative impact is noticed in the decreased Gardiner choice percentage for all Gardiner-supporting information scenarios (PG, DHH, DMH, DMM, DLH, DLM, and DLL), with different levels. Information, in such cases, may be introducing a factor of confusion in light of the higher uncertainty.
- As for group 2, under more reliable information, both males and females reveal similar behavioural trends with respect to information scenarios. A positive influence could be observed for supporting and opposing information scenarios. Nonetheless, females' choice percentages illustrate an increased level of appreciation of disseminated information when compared to males.

- In the presence of information, females' MDT is higher than their corresponding males' MDT. The apparent increase in MDT is more vivid in descriptive information scenarios where a specific recommendation is not provided.

Statistical Significance

To test the statistical significance of gender impact, 2-way ANOVA tests are conducted between male and female choice percentages under the 12 information scenarios, for each reliability group independently. Group 1 results show no significant main effects of gender differences on choice percentages. In other words, the average choice percentages of males or females (under all information scenarios collectively) are not significantly different. However, an interaction effect is reported. This means that the effect of gender differences on choice percentages varies under different information scenarios; differences are scenario specific. This result verifies the preliminary observation regarding the differences in the direction of influence of the Gardiner-supporting information scenarios among males and females under reduced information reliability.

A series of one-way ANOVA tests are performed to identify the scenarios with significantly different choice trends. Four information scenarios reported significant differences: PG, DMM, DLH, DLM. All 4 scenarios clearly support taking the Gardiner. This outcome verifies the preliminary observation of the differences in information influence direction between males and females in case of supporting information scenarios.

On the other hand, no main or interaction effects are reported for the gender factor within group 2. Choice trends for both males and females are estimated to be equivalent. The apparent increase in female compliance percentages is not proven to be significant within the conducted analysis.

Finally, a 2-way ANOVA test is conducted on MDT for males and females under the 12-information scenario for the entire data set. The observed increase in female MDT in descriptive information scenarios is estimated to be insignificant.

6.3.2.3 Impact of Risk Attitude

Drivers' personal characteristics may influence their route choice decisions. One of the personality dimensions that may play a main role in influencing drivers' deliberation behaviour is the "risk attitudes." Risk-averse drivers are naturally more cautious in their choice decisions, unlike risk-takers. In our experimental analysis, subjects' risk attitudes are assessed through the estimation of a risk index for each subject. A higher risk index indicates a more risk-taking attitude. Details of the estimation procedure are previously discussed in section 5.6.1. The effect of risk attitude, represented by the risk index, is the focus of this step of the analysis. Estimated risk indices range from 10 to 22 units. Subjects' route choice measures are clustered into two classes with respect to their risk indices. An arbitrary value of 15 is set as the upper boundary for the lower class. Table 6.5 presents the aggregate choice percentages for each risk class, under each information scenario, under two information reliability levels. Table 6.6 presents the aggregate MDT for each risk class, under each information scenario, for the entire data set.

Table 6.5 Map-based Experiment, %G categorized by Risk Index and Reliability Level

Information Scenario	Group 1 (0.6 reliability)		Group 2 (0.8 reliability)	
	Class 1 Risk Index (10-15)	**Class 2 Risk Index (16-22)**	**Class 1 Risk Index (10-15)**	**Class 2 Risk Index (16-22)**
No-info	92.5	80.0	98.8	81.5
PG	89.6	99.2	98.3	92.6
PLS	53.2	65.6	35.6	31.2
DHH	88.2	91.1	94.7	78.2
DHM	55.8	47.5	43.5	26.7
DHL	29.1	42.6	11.3	17.4
DMH	86.7	91.2	91.2	85.2
DMM	85.8	88.7	95.9	78.7
DML	48.4	49.0	23.2	32.8
DLH	95.4	95.6	98.7	94.8
DLM	91.1	93.8	98.4	94.2
DLL	80.9	91.1	96.0	85.0

Table 6.6 Map-based Experiment, MDT (sec) categorized by Risk Index

Information Scenario	Class 1 Risk Index (10-15)	Class 2 Risk Index (16-22)
No-info	1.5	1.5
PG	1.5	1.3
PLS	1.9	1.6
DHH	2.2	2.0
DHM	2.4	2.0
DHL	2.3	1.7
DMH	2.5	2.0
DMM	2.5	2.0
DML	2.6	1.9
DLH	2.0	1.6
DLM	2.0	1.4
DLL	1.8	1.5

Preliminary Observations:

- A slight decrease in the Gardiner choice percentage - under No-info scenario - is observed for Class 2 (with a higher risk index), for both reliability levels. This result indicates that risk-takers may be more willing to explore alternate, less attractive, routes.
- Within group 1 (lower information reliability), choice percentages reflects a slightly increased level of influence of disseminated information on choice behaviour of Class 2, under most information scenarios. Subjects with a higher risk index tend to comply more with disseminated information, when information reliability is relatively low.
- Alternatively, within group 2, a slight decrease in the level of information influence could be observed for risk Class 2, under most information scenarios. Under increased reliability level, subjects with a lower risk index are more willing to comply with disseminated information.
- Class 1, reveals a generally increased MDT when compared to Class 2. This could be interpreted as a more cautious kind of behaviour; a tendency to deliberate longer to make more mature decisions.

Statistical Significance

Preliminary observation trends match expected ones in terms of the revealed cautious attitude of Class 1 relative to Class 2. However, the observed differences are not statistically significant. The two-way ANOVA tests on choice percentages reveal no main or interaction effect for both reliability levels. In addition, results of a one-way ANOVA test performed on choice percentages of the No-info scenario for each risk class indicates no significant impact. Moreover, for MDT, the main effect of the risk class is significant only under 86% confidence interval, with no interaction.

The insignificant influence of the risk factor, based on the adopted categorization of the estimated risk indices, may have several possible causes. First, the estimated risk index may not fully capture subjects' actual risk attitudes due to the over-simplicity of the conducted personality test. In addition, stated preferences may differ from revealed attitudes. Another cause may be related to the experimental sample characteristics. The homogeneity of the sample of participants, not only from a socioeconomic, and demographic perspectives, but also from a personality profile one, resulted in a narrow span of estimated risk indices. Estimated indices range from 10 to 22, while they may range, theoretically, from 0 to 24. As such, the assessment of the impact of personality-related characteristics in route choice behaviour could be captured more accurately with a cross-sectional type sampling methodology. Moreover, a more sophisticated personality assessment test could be more insightful; comprehensively capturing personality attitudes.

6.4 Mixed Reality En-route Experimental Analysis

Results of the mixed reality experiment are used to portray subjects' en-route diversion behaviour under information. All subjects started the experimental trip based on their personal preference with no informational influence. Prior to reaching the available diversion point, subjects receive descriptive/prescriptive traffic information. The disseminated information is concerned with the second part of the trip; starting from the diversion point until the destination. Choices and deliberation times for both pre-trip (no information) and en-route (with information) decisions are recorded for each simulated trip. The analysis conducted in this section is focussed on en-route divergence behaviour.

Pre-trip choices are consulted to determine drivers' pre-diversion routes. This piece of information is needed for the assessment of the resistance to divergence attitude, as will be explained in detail in section 6.4.2.2.

6.4.1 Data Filtration

An outlier analysis is performed to extract possible sources of noise in the recorded data. Similar to the map-based experimental data filtration, trips with en-route deliberation times exceeding their mean value, for each subject, with more than 3σ, are disqualified. En-route deliberation times are recorded starting from the display of en-route information until the press of the decision button on the steering wheel, as explained in section 5.4.2. An extensively increased deliberation time could be due to subject's distraction; where she/he forgets to press the decision button in time.

During each trip, subjects receive one of six possible en route-information scenarios. Table 6.7 summarizes all en route-information scenarios. Trips starting from the Gardiner are separated from those starting on Lakeshore to capture the effect of the current route on divergence behaviour, i.e. potential propensity of the driver to stay on the current route, exhibiting some reluctance to diverge. Accordingly, en route-choice percentages and MDT are estimated for each subject, for each current route and for each en-route information scenario.

Table 6.7 Mixed Reality Experiment, En-route Information Scenarios Categorization

Information Type	**Information Content [a]**		**Scenario Abbreviation**
	Disseminated Section-based Congestion States		
Descriptive Information	**Gardiner Sec 2**	**Lakeshore Sec 2**	
	H	H	DHH
	H	L	DHL
	L	H	DLH
	L	L	DLL
Prescriptive information	Take Gardiner		PG
	Take Lakeshore		PLS
No information	Drive Safely		No info

[a] H denotes a high travel time (congested state), L denotes a low travel time (uncongested state)

6.4.2 Decision-Factor Analysis

Similar to pre-trip route choice behaviour, en-route diversion behaviour is expected to be influenced by situational as well as personal factors. The focus of this section is to identify the impact trends of some of the key factors and to estimate their level of significance. Three main streams of factors are investigated within our analysis. The first one is concerned with disseminated information in terms of its form, content and reliability level. The second stream is related to the "inertia effect". (Srinivasa and Mahmassani, 2000). While making an en-route decision, drivers seem to prefer to continue their trip on the pre-selected route, thereby resisting diversion recommendations. This is translated to an initial bias towards the current route before the deliberation process starts. Finally, the third stream of decision-factor analysis is focused on the personal dimensions. The scope of this stream is limited to the assessment of gender-related differences in en-route choice attitudes. Risk attitude, represented through risk indices, is disregarded in this phase of the analysis based on the results obtained from the previous phase (refer to section 6.3.2.3).

The statistical significance of all observed patterns is evaluated based on ANOVA testing results. All conducted ANOVA tests are performed under 95% confidence level, unless stated otherwise. Tabulation of results is presented in appendix B.

6.4.2.1 Information Impact

The assessment of the influence of disseminated information on divergence behaviour is conducted by categorizing experimental measures based on information scenarios and information reliability groups. Trips staring on the Gardiner constitute the larger portion of data (about 78%), with a fair representation of all information scenarios. On the contrary, the representation of information scenarios on trips starting from Lakeshore is limited. Thus, continuing on or diverting from the Gardiner Expressway is used as the basis of the analysis of information impacts. Table 6.8 presents the aggregate categorized measures for each information scenario under each reliability level.

Table 6.8 Mixed Reality Experiment, Mean Observed En-route Choice Measures Categorized by Information Reliability Level

Information Scenario	Group 1 (0.6 reliability)		Group 2 (0.8 reliability)	
	%G	MDT (sec)	%G	MDT (sec)
PG	92.9	7.5	94.8	10.5
PLS	41.7	4.6	39.2	8.3
DHH	91.1	4.9	93.6	8.9
DHL	40.6	4.4	24.2	10.8
DLH	100	4.2	97.0	7.5
DLL	100	5.5	97.9	9.4

Preliminary Observations:

- The influence of information content in varying Gardiner choice is evident for both reliability groups. This clearly shows that drivers make use of the provided information to alter their default choice.
- The impact of reliability level on choice percentages is noticeable only in the DHL case. The descriptive information in this case represents an opposing information scenario, in which case more reliable information is more trustful and hence acted upon.
- A substantial impact of information reliability on varying deliberation time frames could be observed. The higher the reliability level the more elaborate the deliberation process.
- The impact of information content on varying deliberation time frames is not apparently observed.

Statistical Significance

A repeated measure 2-way ANOVA test is performed on the Gardiner choice percentages to investigate information significance. This is performed for both reliability groups under different information scenarios. The significance of information content in varying choice percentages is reported to be statistically significant. However, the impact of the 20% difference in information reliability level is estimated to be insignificant in varying subjects' diversion attitudes. A reduced sensitivity of choice percentages to information reliability in the en-route choice context is, thus, revealed. This could be related to the influence of another important factor: the "inertia effect." The inertia effect is simply the intuitive tendency of most drivers to continue on the same route. The interaction between compliance and inertia is significantly recognized in route choice literature as the primary factor driving en-route diversion behaviour (Sirinivasan and Mahmassani, 2000).

The impact of information scenario and information reliability in varying deliberation time frames, reported a different statistical significance trend. While information reliability has a substantial impact on MDT, no significant effect of information content or interaction is reported. The evident increase in MDT under higher information reliability levels reflects a tendency to perform a more serious deliberation process. The accountability of disseminated information stimulates subjects' willingness to make better choice decisions by undertaking an elaborate decision-making process.

6.4.2.2 Impact of Resistance to Diversion

Most drivers intuitively prefer to stay on their current route, unless there is an actual need for diversion. Individual drivers assess the need for diversion based on the magnitude of the perceived gain from diversion. The effect of the current route on choice percentages for identical information scenarios is investigated to analyze the resistance trend. Each of the following four scenarios are tested independently: PG, PLS, DHH, and DHL. The remaining 2 scenarios are disregarded during the analysis due to an insufficient number of observations resulting from the stochastic nature of the experiment. Aggregate choice percentages for the four information scenarios categorized by the current route are presented in Table 6.9.

Table 6.9 Mixed Reality Experiment, En-route %G Categorized by Current Route

Information Scenario	**Current Route**	
	Gardiner	**Lakeshore**
PG	94.5	70.7
PLS	45.2	15.2
DHH	89.6	36.8
DHL	34.9	29.4

Preliminary Observations:

- Reduced Gardiner choice percentages are noticeable for trips starting on Lakeshore, for all information scenarios. This reflects a tendency to resist diversion, as higher percentages of drivers choose the Gardiner if they are already on it, compared to lower percentages choosing the Gardiner if they start on Lakeshore, given the same information (note that all the percentages in Table 6.9 are %G).
- A considerable difference in choice percentages is observed for PG, PLS, and DHH. However, the difference is less for DHL.

Statistical Significance

A set of one-way ANOVA tests is conducted to assess the significance of diversion-resistant behaviour for each information scenario separately. Testing results report a significant difference in choice percentages between trips starting on the Gardiner and those staring on Lakeshore for 3 information scenarios; PG, PLS, and DHH. In other words, subjects tend to resist diversion when perceived travel-time gains are minimal (DHH) or unknown (PG, PLS). On the other hand, when the perceived gain is substantial (DHL), the influence of the current route on choice percentages diminishes to an insignificant level. These results are consistent with the bounded-rationality principle in the route choice literature (Chen and Mahmassani, 1993). The bounded-rationality principle states that drivers divert only when the perceived travel-time gains, from diversion, exceeds a certain threshold level.

6.4.2.3 Gender Impact

Investigating gender differences in diversion behaviour is conducted based on data categorization by gender. The reduced level of significance of information reliability groups on choice percentages precluded the need for creating separate categories for information reliability levels. However, for MDT, data are categorized separately for different information reliability groups. Similar to information significance investigation, data for trips starting on the Gardiner are only used for the intended analysis. Tables 6.10 and 6.11 present the aggregate categorical measures for both %G and MDT, respectively.

Table 6.10 Mixed Reality Experiment, En-Route %G Categorized by Gender

Information Scenario	Males %G	Females %G
PG	94.9	92.6
PLS	51.8	24.2
DHH	92.7	93.6
DHL	40.5	18.7
DLH	98	100
DLL	99	100

Table 6.11 Mixed Reality Experiment, En-Route MDT categorized by Gender

Information Scenario	Group 1 (0.6 reliability)		Group 2 (0.8 reliability)	
	Males	Females	Males	Females
PG	8.6	3.5	12.5	5.5
PLS	5.6	1.2	9.0	6.5
DHH	5.3	3.2	8.1	10.6
DHL	4.5	3.8	11.0	10.4
DLH	4	3.3	9.1	4.5
DLL	6	3.5	11.7	4.6

Preliminary Observations:

- Females' choice percentages reflect an increased level of impact of disseminated information on their diversion attitudes, for opposing information scenarios (DLH, DHL).
- A slight increase in deliberation time frames could be observed for males relative to females under a reduced reliability level (group 1).
- The variation between males' and females' MDT is more considerable under an increased reliability level.

Statistical Significance

The impact of information content in diversion trends of both males and females is assessed using a repeated measures 2-way ANOVA. Testing results, on choice percentages, report no main or interaction effect for the gender factor. However, a significant impact of gender differences, in varying deliberation time frames, is reported under the reduced information reliability level (sub-group 1). The reduced sensitivity of diversion behaviour to the gender factor reflects the dominating impact of situational factors, represented by information provision and current route, over personal profiles, represented only by the gender dimension.

6.5 COMPARATIVE ASSESSMENT: MIXED REALITY VS MAP-BASED EXPERIMENTAL RESULTS

At this point in the analysis, observed route choice trends from both the pre-trip map-based and the en-route mixed reality experimental results could be logically interpreted and related to route choice literature. No severe unexplained deviations are encountered. The final step in this investigation is an assessment of the effect of the experimental procedure on test results. Subjects' route choice attitudes are compared under identical situational conditions for both experimental procedures. For this purpose, pre-trip choice decision measures from both testing procedures under No-info scenarios are compared. As the same test network, with identical traffic patterns, is adopted for both testing procedures, similar choice trends should be expected. However, the precision of the two methods in quantifying those trends is of interest. Figures 6.4 and 6.5 present the results of the choice percentages and MDTs for all subjects using both testing procedures.

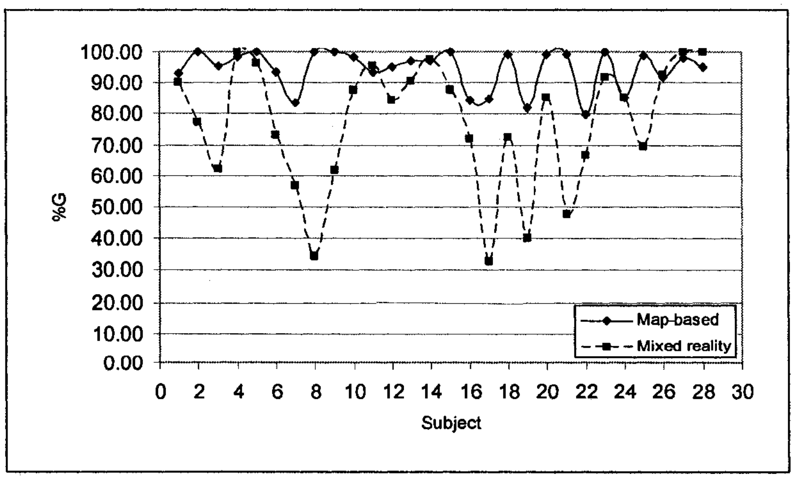


Figure 6.3 Map-based vs. Mixed Reality Choice Percentages

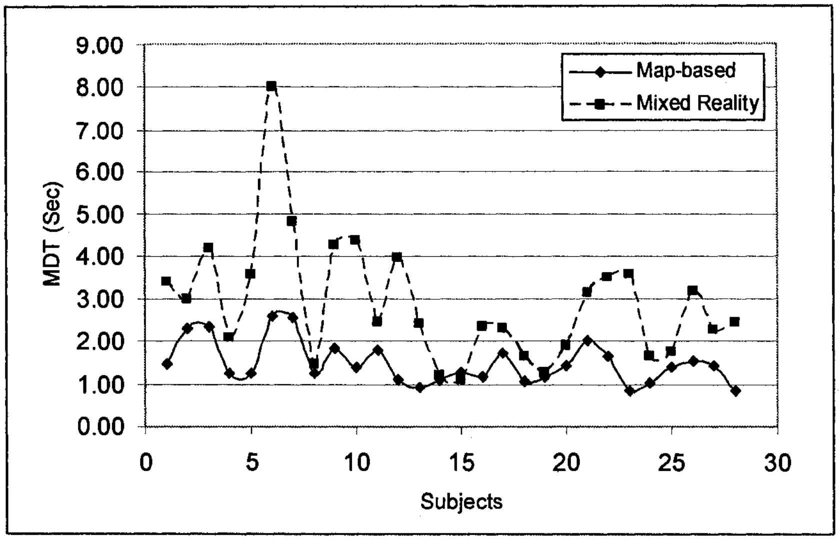


Figure 6.4 Map-based vs. Mixed Reality MDT

Two observations could be clearly depicted from the above figures. First, results from the mixed reality experiment reveal a lower level of preference toward selecting the Gardiner compared to results from the map-based one. Second, the deliberation time frames in the mixed reality experiment are higher than their corresponding map-based ones.

Two one-way ANOVA tests are conducted to verify these preliminary observations statistically. The first is a comparison between choice percentages for pre-trip decisions under No-info scenarios from both experimental procedures. A significant difference is reported between the two testing procedures with respect to choice percentages. The second test, performed on MDT, reports an absolute significant difference. The substantial increase in deliberation times under the mixed reality experiment manifests a desire to make more careful/serious decisions compared to the map-based experiment. In a mixed reality environment, consequences of a choice will be directly experienced. If a driver makes a bad choice, she/he will have to endure congestion and spend actual clock time behind the wheel. The significant decrease in the Gardiner route choice percentage is also a direct outcome of a more mature deliberation process that challenges the thoughtless propensity of sticking to the same choice without actually deliberating.

In summary, results of the experimental analysis indicate that map-based experimental route choice analysis captures the general route choice patterns in a qualitative sense. However, exposing subjects to a simulated driving experience within the mixed reality experimental procedure reproduced more credible quantitative results. The virtual reproduction of the choice environment, in addition to the tangible consequences of choice decisions contribute to a more serious testing environment. Nonetheless, real-time simulations of a large number of experimental trips are very time-consuming, both for participants as well as researchers. Scheduling and conducting of the above experiments required several months of dedicated focus. As such, obtaining large sample sizes within the mixed reality environment is a challenge.

6.6 Concluding Remarks on Experimental Route Choice Results

The analysis of route choice behavioural patterns estimated from the conducted laboratory experiments reveals significant insights that could be grouped into two levels. The first level is concerned with the assessment of decision patterns for each choice context (pre-trip and en-route) independently. Results of the map-based experiment are used for the analysis of pre-trip choice behaviour. The relatively large number of map-based experimental trips, with a considerable representation of all information scenarios, assists in the distinction of various behavioural patterns. A significant information impact in terms of form, content and reliability is reported for pre-trip choice decisions. Subjects' pre-trip choices are significantly altered when receiving traffic information that substantially challenges their expectations. A considerable sensitivity of choice attitudes to the limited variation in information reliability (20%) is observed. In addition, the impact of gender differences in varying choice patterns is significantly observed only under the reduced reliability level.

En-route diversion behaviour, observed from the mixed reality experiment, reveals other insights. The significant impact of information content and current route dominate all other investigated factors. The interaction between compliance and inertia impacts subjects' diversion behaviour. The trade-off is based on the significance of perceived gains from diversion. Minimal and unknown travel time gains stimulate a resistance to diversion attitude, reflecting a bounded-rationality type of behaviour.

The second level of analysis is focussed on the assessment of the value of the experimental procedures as data collecting tools. Three main conclusions are drawn from this analysis: 1) the testing procedure (mixed reality vs. conventional map based) has a significant impact on experimental results, 2) map-based testing procedure is capable of portraying a generic picture of route choice behaviour and is thus suited for qualitative high level assessments, and 3) mixed reality platform has a potential to enhance the realism of in-lab simulated route choice experiments, hence improving the credibility of collected data.

7 DFT ROUTE CHOICE MODEL PARAMETER ESTIMATION

7.1 PRÉCIS

The focus of this chapter is on estimating the values of the DFT route choice model parameters. Route choice observations collected from the simulated driving experiments (discussed in chapters 5, 6, and 7) are used for calibration. Estimation of model parameters is based on the minimization of prediction errors using Genetic Algorithms (GA) as an optimization tool. Predictions are based on computer simulation of route choice behaviour using the DFT model. As such, a GA-based optimization platform is developed in this research to serve as the parameter estimation tool. A detailed description of the adopted estimation methodology is presented. Finally, estimated results and insights conclude this chapter.

7.2 GA: AN EVOLUTIONARY APPROACH FOR PARAMETER ESTIMATION

Estimation of DFT route choice model parameters is formulated as an optimization problem that involves minimization of errors between predicted and observed measures (Diederich, 2003, Diederich and Busemeyer, 1999). While observed measures (choice probabilities and MDTs) are collected through in-lab simulated route choice experiments, model-based choice prediction can be achieved using two different approaches. The first approach is based on closed-form analytical prediction. In this approach, predictions are outputs of formulas mathematically drived from the basic DFT structure based on some approximating assumptions (Busemeyer and Townsend, 1993, Diederich, 1997 and Busemeyer and Diederich, 2000). The second approach relies on simulation, where predicted measures are outputs of a computer-simulation of the deliberation process (Roe et al., 2001). While mathematical formulas are more tangible to deal with, the power of the simulation-based approach relies on its preservation of all of the theoretical model characteristics. Simulating the deliberation process limits the amount of lost information during mathematical approximations. With the current advancements in computer-based simulations, the simulation-based approach is deemed more appropriate for prediction purposes of the problem in hand. However, classical optimization techniques are not suited to deal with simulation-based optimization problems. Therefore, a non-classical evolutionary-based optimization technique is considered for the simulation-based parameter estimation problem.

Evolutionary Algorithms (EA) are search algorithms that mimic the natural fitness-based selection process that is well known in evolutionary theories. EA rely on the concept of survival of the fittest (or most optimum) to guide a randomly generated population of solutions towards improvement. As each new generation of solutions is created, bits and pieces of the fittest members of the previous generations are reused and recombined (Goldberg, 1989).

Genetic algorithms (GA) are one of the basic forms of EA. GA were first investigated by John Holland (1975) at the University of Michigan. Further studies were carried out by his students (for example, De Jong, 1975 as indicated by Whitley, 1994). For the purpose of parameter estimation, GA are used as function optimizers. The strength of GA as a stochastic search-optimization technique stems from its global searching perspective. Many classical optimization methods transfer from a single point in the decision space to the next using some transition rule. These point-to-point methods can be trapped in false peaks in multimodal search spaces. Alternatively, GA works from a rich database of points simultaneously, climbing many peaks in parallel. GA operations are not based on gradient information. Thus, they are highly applicable to problems having non-differentiable functions, as well as functions with multiple local optima (Whitley, 1994).

The application of GA within many transportation optimization problems reports advantages in dealing with non-convexity, locality and complexity of such problems (Kattan, 2004). The adopted simulation-based approach for DFT route choice prediction features a complex and multi-dimensional solution space. As such, the adoption of GA as an optimization tool for model parameters estimation is considered.

7.3 GA-BASED PARAMETER ESTIMATOR PLATFORM

The specifics of the problem in hand require the development of a tailored GA-based optimization tool. A computer program is coded in a Visual Basic environment for this purpose. A basic GA architecture is adopted. Classical GA operations are considered. For a comprehensive description of the basic GA operations in addition to more sophisticated GA implementations the reader is referred to Goldberg (1989).

The conceptual DFT route choice modelling framework describes three deliberation models: no information, descriptive information and prescriptive information models. Each deliberation model has its own schematic, decision variables and decision parameters. Accordingly, three different versions of the GA-based optimization program are developed. This section presents an overview of the adopted optimization platform.

7.3.1 GA Architecture

The fundamental structure of all GAs can be described through the following simplified algorithm:

```
BEGIN
Generate a new population of solutions
While terminating conditions are not met DO
   Evaluate the solutions
   Select the better solutions
   Recombine solutions using genetic operators
END
```

The procedures involved in: population generation, selection of best solutions, and re-combinations using genetic operations, vary tremendously across various genetic algorithms. Figure 7.1 illustrates the GA procedure for estimating DFT route choice model parameters. The following sections discuss each procedure in further detail.

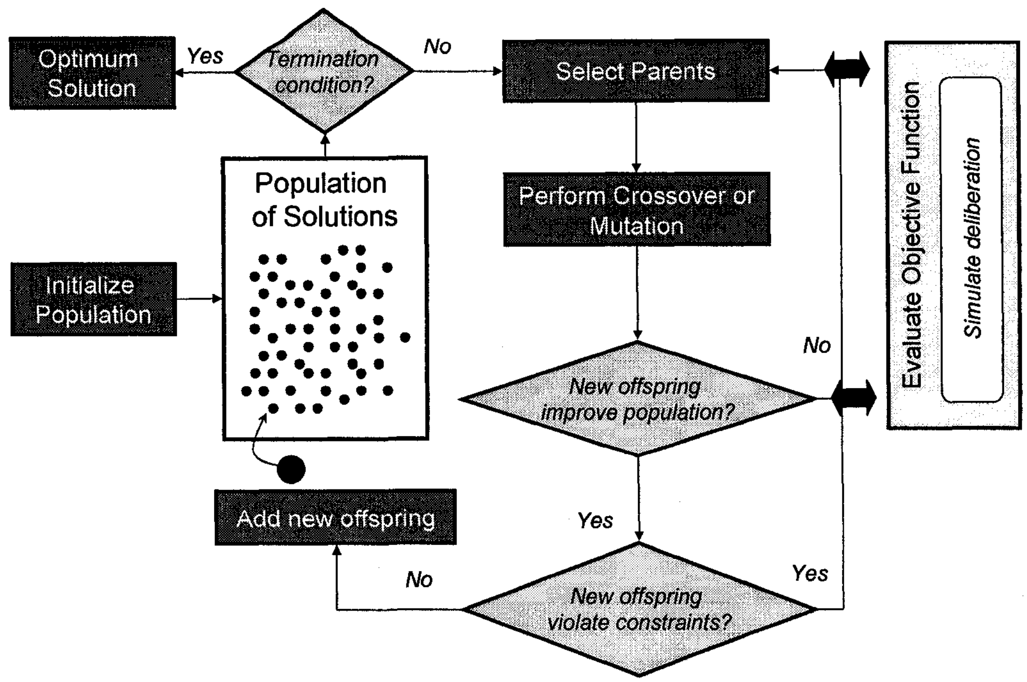


Figure 7.1 GA Optimization Architecture

7.3.2 GA Implementation

7.3.2.1 Problem Encoding

This step translates a solution into a "string" or "chromosome" that can be manipulated by the GA. Binary encoding is utilized in the GA. Binary encoding allows relatively simple genetic manipulations of the chromosome to take place. Each chromosome represents an entire solution. Each chromosome is divided into a number of stretches (bit sets) corresponding to the number of parameters to be estimated. The developed architecture allows the selection of various bit encodings for each parameter (128, 256, 512, and 1024 encodings). Larger bit encodings divide the solution space into smaller search intervals but tend to increase computational complexity. Figure 7.2 presents an example of a 128 bit encoding of GA chromosome.

W_{TT}	1	0	0	0	0	1	1	0
W_D	1	1	1	0	0	0	0	0
W_F	0	0	0	1	0	1	0	1
S_{ii}	0	0	1	1	1	1	0	1
S_{ij}	1	0	1	0	1	1	0	0
π_{TT}	0	0	1	1	0	1	0	1
π_D	1	0	0	0	0	1	1	0
π_F	1	1	0	0	0	0	0	0
ΔP	1	0	0	0	0	0	0	1
θ	1	1	1	1	1	0	0	0

Figure 7.2 GA Chromosome

7.3.2.2 Population Initialization

Genetic algorithms work with a population of solutions. The initial population is a completely randomized set of solutions that lie within the feasible solution space. The developed architecture allows various population sizes to be manipulated. Larger population sizes tend to increase computational complexity. Smaller sizes run the risk of entrapment in local minima.

7.3.2.3 Parent Selection

Genetic algorithms rely on concepts of survival of the fittest. Based on this concept, more optimal solutions have higher chances of selection during the population's evolution. A Roulette-Wheel selection procedure is adopted. Each of the population solutions (chromosomes) is represented on the roulette wheel through a sector that is proportional to its estimated fitness value. Selection of parent chromosomes is undertaken using "stochastic sampling with replacement" (Whitley, 1994). The process of solution evaluation can be as straightforward as calculating a simple formula or as complicated as running a simulation experiment. The GA-based parameter estimation runs a deliberation process simulation to evaluate the fitness of each solution as described in later sections.

7.3.2.4 Genetic Operator

After candidate parents are selected they are manipulated using genetic operators. Crossover operators exchange genes between parent chromosomes, hence, produce 2 new solutions. Random single-point crossover is used in the GA.

Figure 7.3 illustrates how this crossover takes place.

Parent A	**1**	**1**	**0**	**1**	*0*	*0*
Parent B	*0*	*1*	*1*	*1*	**1**	**0**

Crossover Point

Offspring 1	**1**	**1**	**0**	**1**	**1**	**0**
Offspring 2	*0*	*1*	*1*	*1*	*0*	*0*

Figure 7.3 Example of a Single Point Crossover with a Binary Encoding

In addition to crossover, mutation is commonly used as a genetic operator. Mutation involves the random alteration of a bit value in the chromosome. The main motivation for using mutation is to allow for the exploration of new areas in the solution space, and hence, preventing premature convergence. Small population sizes, in particular, are more prone to getting trapped in false peaks (Whitley, 1994).

7.3.2.5 Evaluating the New Solutions

Crossover and mutation create a new population of solutions. Each solution must be evaluated to ensure that:

- It is not worse than the worst solution in the population, and
- It is a feasible solution (i.e., it does not violate any of the optimization constraints).

If both conditions are met, the new solutions are introduced into the population by replacing the worst solutions. This ensures a relatively quick conversion rate of the algorithm. Solution evaluation is based on estimation of a fitness function. The fitness function is a quantification of the predictive accuracy of the DFT route choice model based on the set of parameter values being evaluated. As such, the evaluation of a solution point is achieved in three steps: (1) deliberation-processes simulation, (2) objective-function evaluation, (3) fitness-function evaluation, described in the following sections.

1. Deliberation processes simulation

Prediction of route choice percentages and MDTs for each of the information scenarios, shown in Table 7.1, is performed through repeated simulations. For each set of model parameters being evaluated, i.e. for each chromosome, several simulations are performed to produce the choice percentages and MDTs statistics under each scenario. The number of repeated simulations is user-defined. Specification of the appropriate number of repeated simulations is a trade-off between accuracy and computational complexity. As the operation of GA is based on population evaluation rather than point evaluation, increased number of simulations per information scenario dramatically increases the computational complexity. On the other hand, a very small number of simulations jeopardizes the accuracy of the estimation process and precludes convergence.

Specification of an appropriate number of simulation runs, for the problem in hand, is performed on a compromise basis. Results of the sensitivity analysis, on the variability of route choice measures with varying numbers of simulation runs, presented in section 5.5, report a significant decrease in estimated variability beyond 50 simulations (refer to figure 5.4). Based on observed computational time frames of a set of preliminary GA runs, 100 simulations per information scenario are used. For instance, under descriptive information, the total number of simulations in the calibration process = number of information scenarios (i.e. 4) x number of simulations per scenario (i.e. 100) x number of chromosomes per generation x number of generations to convergence, not including inferior and infeasible chromosomes.

The simulation of a deliberation process is simply a second-by-second estimation of the evolution of decision-maker preferences based on the theoretical abstraction of DFT. The conceptual framework of each deliberation process is adopted for the simulation purpose. While decision variables (*Anticipated State Probabilities, ASPs, and Attribute Payoffs, M*) values are pre-defined through the experimental setup, decision parameters are determined by the GA optimization (refer to equation 3.1).

At each time step, the decision maker integrates his previous evaluations with his instantaneous one. The instantaneous evaluation is based on the payoffs of a stochastically-chosen attribute under a stochastically-defined congestion state. A time-step value of one second is considered throughout the simulation process. A choice decision and a decision time are determined through either an upper-threshold bound or an externally imposed decision time, based on the adopted decision rule. Outputs of the simulation module are predicted route choice percentages and MDTs for each parameter set (chromosome) for each information scenario of the deliberation model in hand.

Table 7.1 En-route Information Scenarios Categorization [b]

Information Type	**Information Content [a]**		**Scenario Abbreviation**
	Disseminated Section-based Congestion States		
	Gardiner Sec 2	**Lakeshore Sec 2**	
Descriptive Information	H	H	DHH
	H	L	DHL
	L	H	DLH
	L	L	DLL
Prescriptive information	Take Gardiner		PG
	Take Lakeshore		PLS
No information	Drive Safely		No info

[a] H denotes a high travel time (congested state), L denotes a low travel time (uncongested state)
[b] This table is a reproduction of Table 6.7

2. *Objective function*

Parameter estimation is based on the minimization of prediction errors. Thus, a formulation of prediction error has to be defined. Prediction errors are represented in two dimensions: choice percentages and MDTs. As both measures are different in units, an overall percentage-based error is considered.

Evaluation of the prediction accuracy of a specific solution point (chromosome) is based on the estimation of the Mean Absolute Percent Error (MAPE) (equation 7.1). MAPE averages all errors from all information scenarios within the deliberation model under investigation. Errors in choice percentages and MDTs are given equal weight in the MAPE calculation. Averaging of prediction errors (difference between DFT model outputs and the mixed-reality experiment results) from different information scenarios is based on a weighted scheme. Observed measures, for each information scenario, are based on data recorded from a set of experimental trips in the mixed-reality simulator with identical information scenarios. Due to the stochastic nature of the experiments, the number of experimental trips conducted in the mixed-reality simulator under each information scenario is different. The significance of observed measures is dependent on the size of the respective data set. As the number of experiments increase, the power of observed measures is expected to increase as well. As such, prediction errors from each information scenario are weighted based on its corresponding sample size relative to the total sample size of the deliberation model in hand.

$$MAPE = \sum_{i=1}^{n} w_i * [\frac{1}{2} * \left|\%G_{predicted}(i) - \%G_{observed}(i)\right| + \frac{1}{2} * \frac{\left|MDT_{predicted}(i) - MDT_{observed}(i)\right|}{MDT_{observed}(i)}] \quad (7.1)$$

$$w_i = \frac{N_i}{N_T} \quad (7.2)$$

Where:

- n, is the number of information scenarios of the deliberation model under investigation
- $\%G_{predicted}(i)$, is the Gardiner-predicted choice percentage under information scenario i.
- $\%G_{observed}(i)$, is the Gardiner-observed choice percentage under information scenario i.
- $MDT_{predicted}(i)$, is the predicted mean deliberation time under information scenario i
- $MDT_{observed}(i)$, is the observed mean deliberation time under information scenario i.
- w_i, weight assigned to the estimation error of information scenario i.
- N_i, is the number of conducted mixed-reality simulated route choice experiments under information scenario i, from which observed measures are estimated.
- N_T, total number of conducted in-lab simulated route choice experiments for the deliberation model under investigation.

3. *Fitness function*

The fitness of a solution point (chromosome) reflects its goodness or adequacy. As the prediction error decreases, the solution fitness increases. Thus, a simple transformation of the MAPE to its reciprocal value is adopted as a measure of fitness.

7.3.2.6 Termination Criteria

Termination of the optimization process is based on two criteria: degree of population convergence, and number of generations. The degree of population convergence at a given generation is measured by the difference between the objective function values of the best and the worst solutions of the population, as a percentage from the best value. The optimization process is terminated when the population converges to a pre-defined threshold. The value of the convergence threshold is user-defined. Alternatively, an upper bound to the number of GA generations is defined to terminate the optimization process, in case the population did not converge to the pre-defined threshold.

7.4 Detailed Description of the Parameter Estimation Methodology

Estimation of the route choice model parameters is based on data collected from the mixed reality experiments. Based on the significant impact of the testing procedure on experimental results (discussed in Chapter 6), map-based results are excluded and only mixed reality experimental observations are considered. Given the homogenous and limited sample size of test drivers, however, estimated parameter values are considered potential values for a specific class of drivers. Further generalization of the model to all classes of drivers will require wider-scope experimentation, which is beyond the scope of this research.

7.4.1 Mapping Experimental Setup to the Route Choice Model Conceptual Framework

The conceptual framework of our route choice model, discussed in chapter 3, outlines the abstraction of three deliberation processes: a basic case with no information, a descriptive information case, and a prescriptive guidance one. The three processes are represented in the mixed reality route choice experiments. In the pre-trip choice situation, drivers have to choose between the Gardiner (G) and Lakeshore (LS), without information provision. En-route deliberation processes are concerned with the choice situation at the decision node with either descriptive or prescriptive information provision. As such, the following three deliberation models are considered: (1) **P**re-trip **N**o Information Deliberation model (**PN-model**), (2) **E**n-route **D**escriptive-Information Deliberation model (**ED-model**), and (3) **E**n-route **P**rescriptive- Information Deliberation model (**EP-model**). The operation of each model entails the definition of a schematic representation, decision variables, and decision parameters as described in the following sections.

7.4.1.1 Schematic Representations

In the PN-model three congestion levels are perceived for each of the two alternative routes (H, M, and L). The combination of congestion levels results in nine possible anticipated congestion states for each choice/action. Figure 7.4 displays the schematic representation of the PN-model.

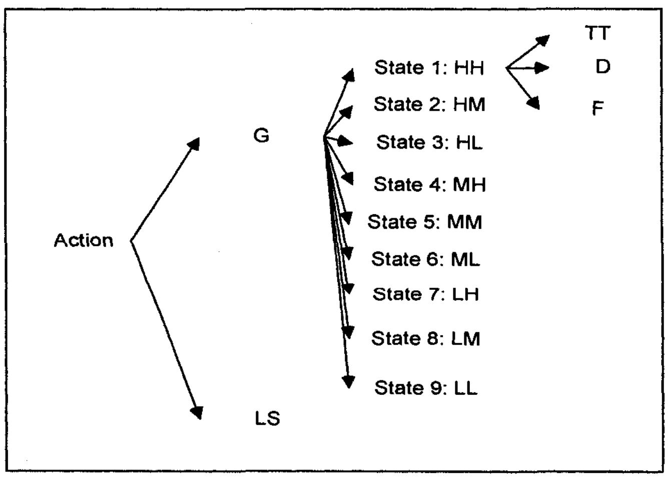


Figure 7.4 PN-model Schematic Representation

En-route deliberation models are concerned only with the second half of the trip. According to the experimental setup, only 2 congestion levels are perceived for the second portion of the trip (H, and L). As such, both en-route deliberation models incorporate four possible congestion states. However, the number of considered attributes varies depending on the type of disseminated information. Only the basic choice attributes (Travel Time (TT), Distance (D), and Freeway usage (F)) are considered for the ED-model. A fourth attribute (Compliance (C)) is added to the EP-model. Figure 7.5 and Figure 7.6 display the schematics of both en-route deliberation models.

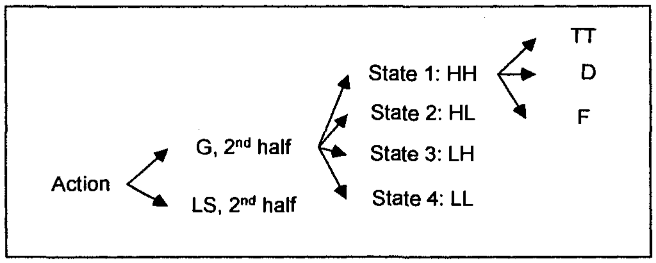


Figure 7.5 ED-model Schematic Representation

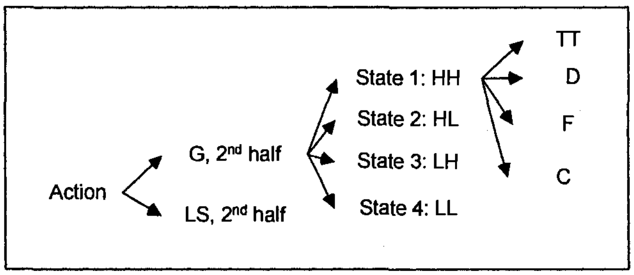


Figure 7.6 EP-model Schematic Representation

7.4.1.2 Decision Variables

Decision variables, on the other hand, are abstract representations of the experimental setup in terms of attribute payoffs (*M*) and anticipated state probabilities (*ASPs*). Attribute absolute values are based on the experimental setup (section 5.3). Attribute payoffs are estimated using payoff formulations (sections 3.6.2.2, and 3.7.1.2). Mean values of travel time distributions, for different congestion states are used for the estimation of the travel time attribute payoff. Distances and freeway usage attribute payoffs are directly estimated from the test network characteristics. Table 7.2 and Table 7.3 present the absolute and the payoff values for pre-trip and en-route decision attributes, respectively.

Table 7.2 DFT Route Choice Model Pre-trip Decision Attribute Values

Attribute		G		LS	
		Absolute value	Payoff value	Absolute value	Payoff value
TT	H	12.00 min	1.82	16.00 min	2.42
	M	9.30 min	1.41	12.00 min	1.82
	L	6.60 min	1.00	8.00 min	1.21
D		8340.00 m	1.00	8432.00 m	1.01
F		8340.00 m	1.00	0.00 m	0.00

Table 7.3 DFT Route Choice Model En-route Decision Attribute Values

Attribute		G		LS	
		Absolute value	Payoff value	Absolute value	Payoff value
TT	H	5.80	1.87	7.50	2.42
	L	3.10	1.00	3.50	1.13
D		3925.00	1.22	3224.00	1.00
F		3925.00	1.00	0.00	0.00
C[a]		1 or 0		0 or 1	

[a] compliance attribute is considered only in EP-model.

Experience-based anticipated congestion level probabilities are directly estimated from the experimental traffic condition controls. A probability value is assigned to each congestion level of each alternative route (for the pre-trip choice context: $Prob\text{-}H_i$, $Prob\text{-}M_i$, $Prob\text{-}L_i$, where $Prob\text{-}H_i + Prob\text{-}M_i + Prob\text{-}L_i = 1$, i=1 to 2 alternatives). Table 7.4 and Table 7.5 present anticipated congestion level probabilities for each alternative route, for pre-trip and en-route deliberation models, respectively. Based on the experimental setup, anticipated congestion level probabilities for all route sections are manipulated independently. As such, *ASPs* are estimated by combining the corresponding anticipated congestion level probabilities ($ASP_{HH}=Prob\text{-}H_1*Prob\text{-}H_2$, $ASP_{HL}=Prob\text{-}H_1*Prob\text{-}L_2$...etc). On the other hand, Information-based anticipated congestion level probabilities are direct translations of the content of descriptive information.

Table 7.4 Pre-trip Anticipated Congestion Level Probabilities

Congestion Level	Experience-based Probability	
	G	LS
H	0.36	0.16
M	0.48	0.48
L	0.16	0.36

Table 7.5 En-route Anticipated Congestion Level Probabilities

		G		LS	
		H	L	H	L
Experience-based Probability		0.6	0.4	0.4	0.6
Information-Based Probability [a]	DHH	1	0	1	0
	DHL	1	0	0	1
	DLH	0	1	1	0
	DLL	0	1	0	1

[a] Information-based congestion probabilities are considered only in ED-model.

7.4.1.3 Decision Parameters

Decision parameters are the subject of the calibration process. A GA-based parameter estimation technique is adopted as described earlier in this chapter. Parameter estimation is based on the minimization of predicted versus observed choice measures. Table 7.6 summarizes the decision parameters that need to be estimated for each of the three considered deliberation models.

Table 7.6 DFT Route Choice Model Decision Parameters

PN-model	ED-model	EP-model
1. W_{TT}, Travel Time weight	1. W_{TT}	1. W_{TT}
2. W_D, Distance weight	2. W_D	2. W_D
3. W_F, Freeway Usage weight	3. W_F	3. W_F
4. π_{TT}, Travel Time attention probability	4. π_{TT}	4. π_{TT}
5. π_D, Distance attention probability	5. π_D	5. π_D
6. π_F, Freeway Usage attention probability	6. π_F	6. π_F
7. $P_G(0)$, Gardiner initial preference strength	7. $P_G(0)$	7. $P_G(0)$
8. $P_{LS}(0)$, Lakeshore initial preference strength	8. $P_{LS}(0)$	8. $P_{LS}(0)$
9. S_{ii}, i=1 to 3. Self-connections (diagonal elements of feedback matrix)	9. S_{ii}	9. S_{ii}
10. S_{ij}, i=1 to 3, j=1 to 3, i≠j. Interconnections (off-diagonal elements of feedback matrix)	10. S_{ij}	10. S_{ii}
11. θ, Threshold bond	11. θ	11. θ
12. σ_ε, Residual error probability distribution parameter.	12. σ_ε	12. σ_ε
	13. W_{info}[a]	13. Wc[b]
		14. π_C[b]

[a] Information weight in congestion state perception
[b] Compliance attribute

7.4.2 Data Aggregation

Each individual is different and hence the estimation of subject-specific parameters could be considered the ideal theoretical approach to adopt. This entails the availability of a fairly large number of choice observations for each subject under each information scenario. Obtaining a large set of observations through real time simulations is very time-consuming and hence is beyond our experimental scope. Moreover, even with subject-specific parameters an aggregation methodology is required for generalization purpose. A large cross-sectional-type sample is required for this type of analysis.

Alternatively, the adopted parameter estimation methodology is based on the use of aggregate observations. Observed data are categorized into a number of homogenous groups. Aggregate observations from each group are used to estimate group-specific parameters. Data categorization is based on the results of the statistical analysis, presented in Chapter 6. Three factors are reported to have significant impacts on pre-trip and/or en-route choices: information characteristics, gender differences and inertia effect.

The categorization of observed data is summarized in Figure 7.7. Data are grouped into two main groups: males and females. Each group is further divided into two sub-groups: sub-group 1 with 0.6 information reliability level, and sub-group 2 with 0.8 information reliability level. Within each sub-group, observations from different deliberation situations are separated (pre-trip, en-route descriptive information, and en-route prescriptive information situations). Moreover, within each deliberation situation, observations are categorized according to information scenarios. For pre-trip choice decisions, only one information scenario (no information) is available through the mixed reality experimental data. As for en-route decisions, there are two information forms (descriptive and prescriptive) with six information scenarios (DHH, DHL, DLH, DLL, PG, PLS). Trips starting from the Gardiner are only used for en-route parameter estimations, as it represents the largest portion of data with a representation of all scenarios.

A data set for estimation and another for testing are extracted from each cluster of observations, with a ratio of 3:1 respectively. The only exception for the estimation/testing categorization is sub-group 1 of the female group. The limited sample size for this sub-group precluded the extraction of a testing set. Finally, choice percentages and MDTs are estimated, as dependent variables, for each sub-set of observations. Based on the above categorization methodology, decision parameters are estimated, for each sub-group, for each deliberation model (PN-model, ED-model, and EP-model). Within each deliberation model, different information scenarios represent different decision variables (different independent variables).

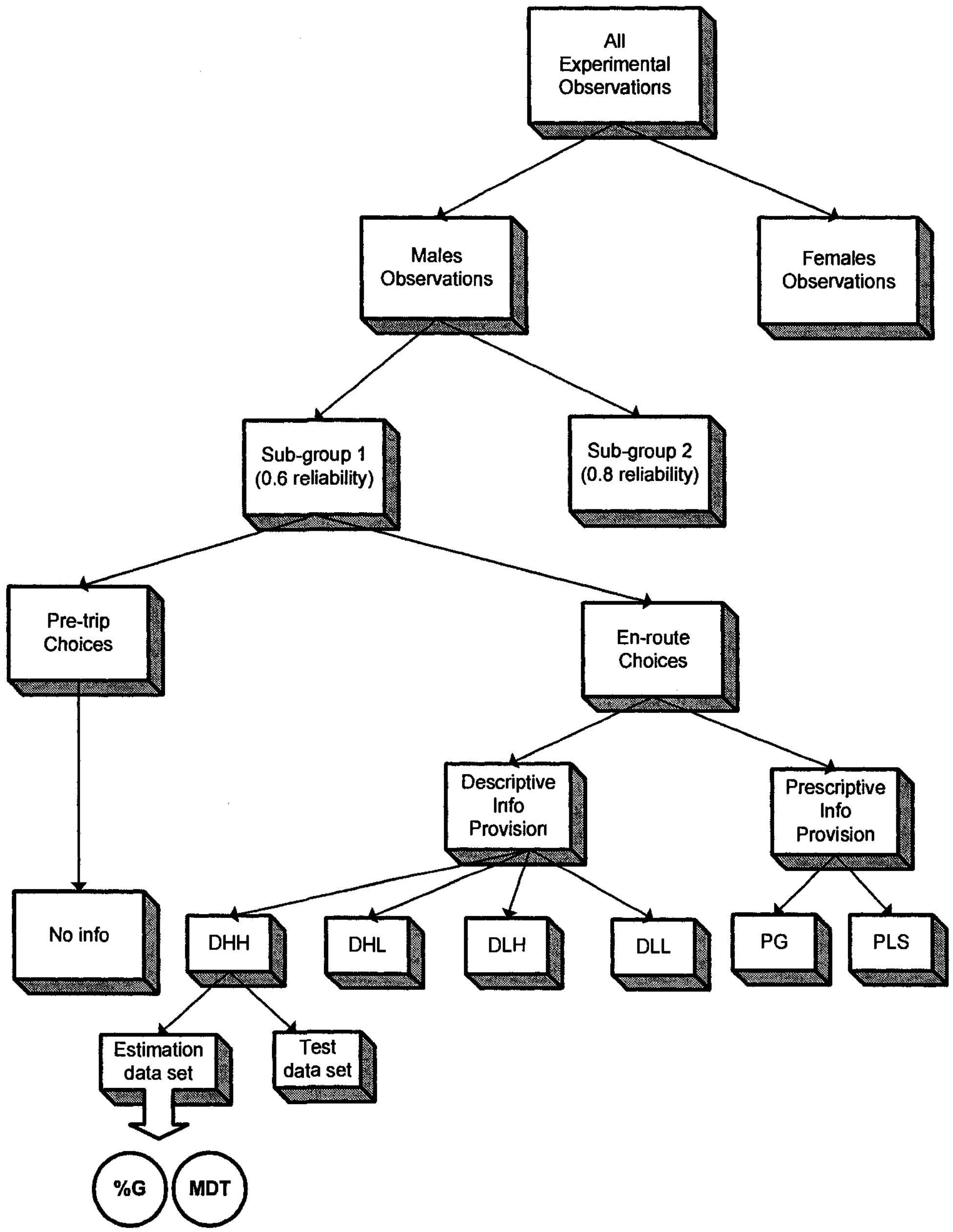


Figure 7.7 Observed Data Categorization for Parameter Estimation

7.4.3 Parameter Estimation Assumptions

7.4.3.1 General Assumptions

The following assumptions are adopted throughout the parameter estimation procedure for all deliberation models:

- Since there are only two choice options, initial preference strengths ($P_1(0)$ and $P_2(0)$) are substituted by a single value representing the initial preference strengths difference (ΔP). Based on the experimental observations, the pre-deliberation bias consistently takes the Gardiner side for the "no information" pre-trip choice decisions as well as for the en-route divergence decisions.

  $P_G(0) = \Delta P$

- Based on many psychological studies, the values of the self-connections (S_{ii}) of the feedback matrix are assumed to be positive and equal (Diederich, 2003, Busemeyer and Diederich, 2002, and Roe et al., 2001).

  $S_{11} \in [0, 1]$

  $S_{11}=S_{22}=S_{33}$

- Interconnection values (Sij) are assumed to be negative and equal for all alternatives combinations (Roe et al., 2001).

  $S_{11} \in [-1, 0]$

  $S_{11}=S_{22}=S_{33}$

- Based on DFT literature, the Eigen values of the feedback matrix (S) are restricted to less than 1 to ensure system stability (Busemeyer and Diederich, 2002).
- Attribute attention probabilities (π's) are assumed to be time invariant (Diederich, 2003).
- The residual error is neglected during the simulation of all deliberation processes within the GA-based parameters estimation. The GA estimation procedure focuses on searching for the optimal parameters despite the noise in the aggregate observations. Incorporation of a random error term within this approach may magnify the noise, distracting the search for an optimal solution.

7.4.3.2 *Within Gender Group Assumptions*

The following assumptions are considered during the estimation of sub-group decision parameters, within each gender group. These assumptions impose some reasonable restricting similarities on estimated parameters. This in turn, reduces the number of parameters that need to be estimated. Figure 7.8 summarizes the assumed restricting similarities using a colouring scheme.

- Attribute weights (W_{TT}, W_D, and W_F) are assumed to be constant across all deliberation models of both information reliability sub-groups. Attribute weights are concerned with the normalization of attribute payoffs relative to their significance for the decision-maker. The significance of the values of attribute payoffs are expected to be more individual-specific than situational-specific.
- Attribute attention probabilities (π_{TT}, π_D, and π_F) of PN-model and ED-model are assumed equal for both information reliability sub-groups. Attribute attention probabilities reflect the relative importance of considered attributes to the decision-maker. The more important the attribute is, the more likely it comes into focus at any point in time. Attribute attention probabilities must sum up to unity for any deliberation model. Both PN-and ED-models consider the same attributes (TT, D, and F), whereas an EP-model considers a forth one (C).
- Feedback matrix (S) is assumed to be constant across all deliberation models of the same gender group. The feedback matrix provides memory of previous states as well as competition between alternatives. Feedback rates are expected to be individual-specific.
- The entire gender group data are aggregated for the PN-model. Sub-group categorization is based on information reliability. With no information provision, no sub-group categorization is required.

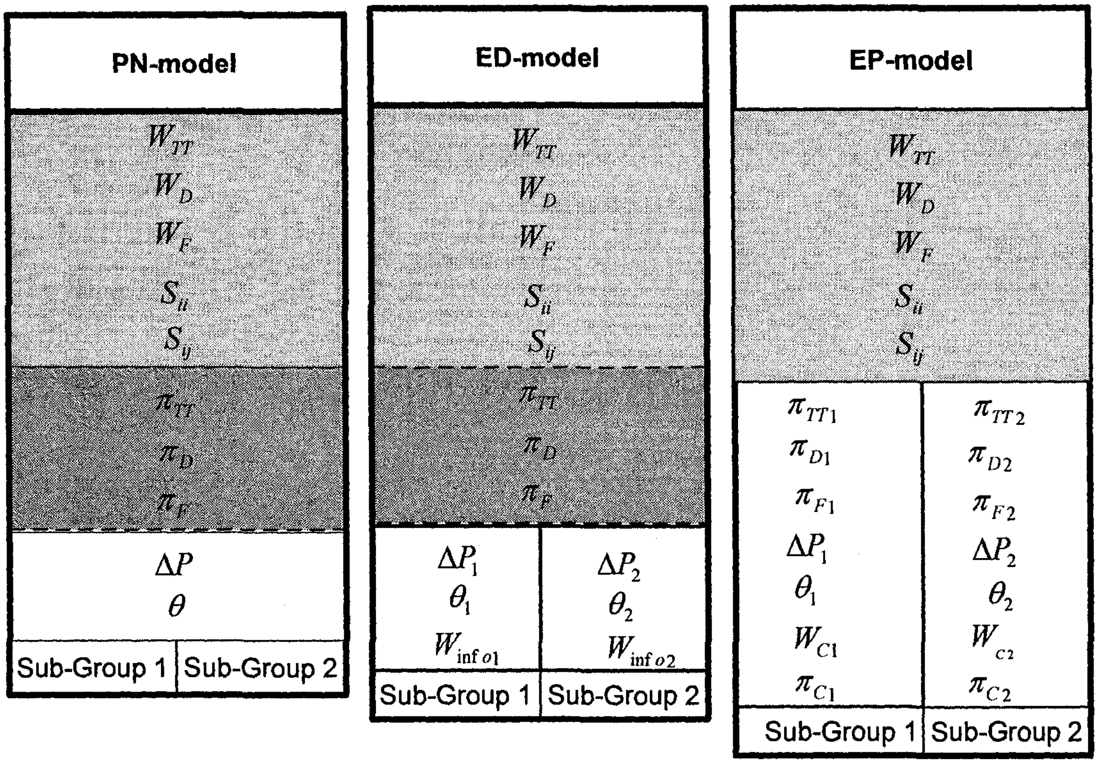


Figure 7.8 Within Group Assumed Restricting Parameter Similarities

7.4.4 Multilevel Step-wise Parameter Estimation Framework

The methodology adopted in estimating deliberation model parameters has two main dimensions. First, there is the within-deliberation-model dimension; concerned with the estimation of parameters for a specific deliberation model. A multilevel (a sub-group level, and a group level) estimation approach is adopted for that purpose. Second, the between-deliberation-model dimension; where assumed similar value parameters are transferred from one deliberation model to the other in a step-wise approach. Figure 7.9 presents the overall estimation framework. The same estimation framework is adopted for both gender groups, independently. The following sections discuss the details of the adopted framework.

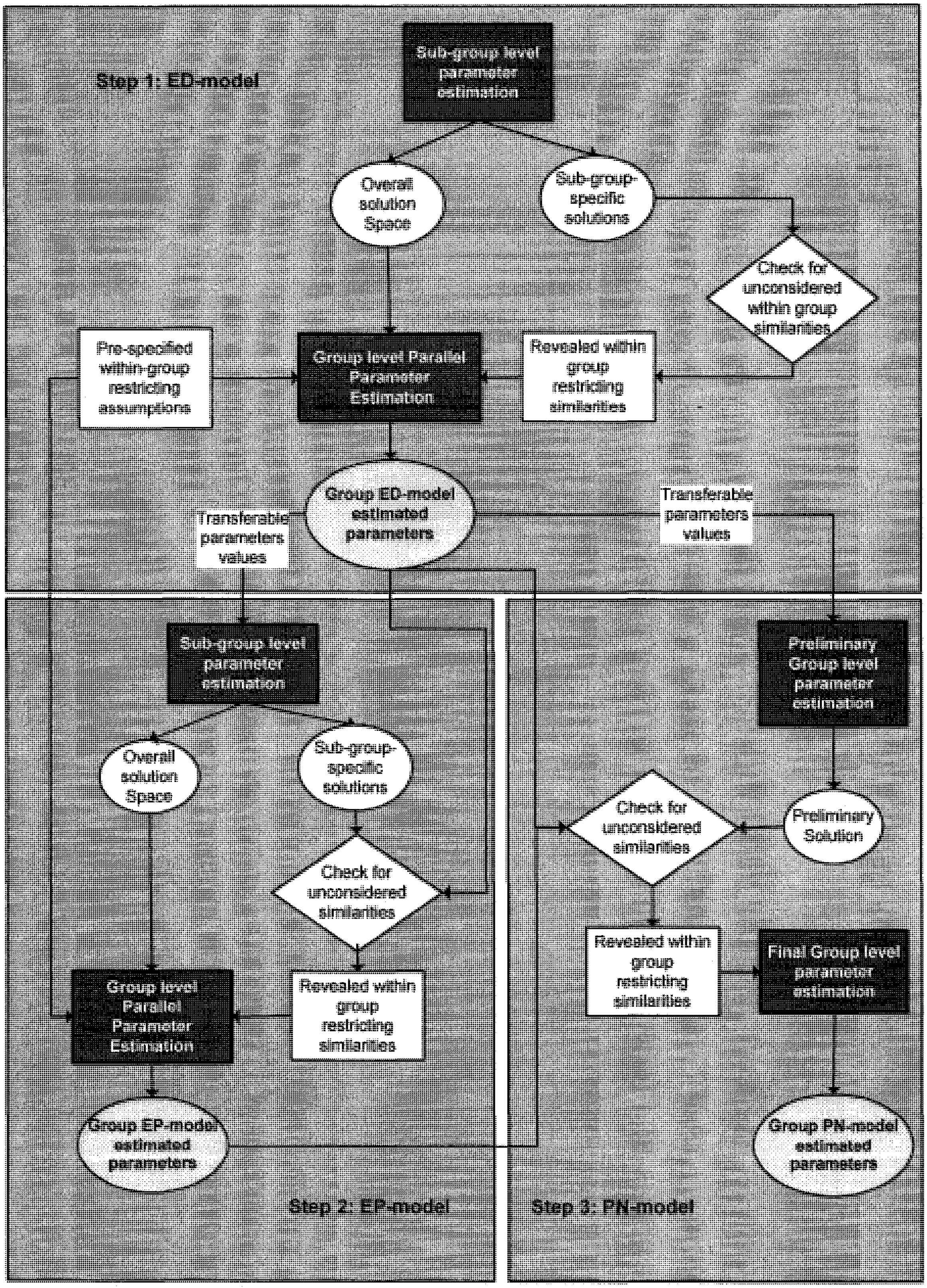


Figure 7.9 Multilevel Stepwise Parameter Estimation Framework

7.4.4.1 Within Deliberation Model Dimension

Estimation of decision parameters within each deliberation model of a gender group is the focus of this section. As discussed previously, each group is further divided into two sub-groups, according to their information reliability level. Based on the pre-defined assumptions, a number of decision parameters are assumed to be equal for both sub-groups (refer to Figure 7.8). As such, the estimation of decision parameters for both sub-groups of a given gender group needs to be performed concurrently in a parallel manner. The large number of parameters that need to be estimated within a parallel-estimation procedure magnifies the problem solution space. To reasonably limit the solution space and thereby guide the GA-based search to a near-optimum solution, a multilevel estimation approach is adopted. In the multilevel approach, parameter estimation is performed on two levels: (1) a sub-group level, and (2) a group level. In the following sections, each level of estimation is discussed in detail. Figure 7.10 presents a schematic of the adopted multilevel estimation approach. It should be noted that the scope of the multilevel estimation approach is restricted to each deliberation model independently. Interactions between deliberation models are discussed afterwards.

1. *Sub-group level parameter estimation*

In the sub-group, parameter estimation level, the best estimated solution and a feasible solution space are defined for the decision parameters of the deliberation model. This is performed independently for each sub-group. Only the general estimation assumptions (discussed in section 7.4.3.1) are considered during this level of estimation. Group-restricting similarities are overlooked at this point. The estimation procedure adopts a GA-based coarse-to-fine search procedure. The coarse-to-fine search is concerned with defining an upper and a lower bounding value for each of the model parameters. A series of extensive runs of the GA estimator is conducted within varying parameter solution space boundaries. Boundary manipulation starts from a wider range and moves toward a narrower one. Subsequently, the best solution is identified within the defined boundaries. A feasible solution space is then restricted to the vicinity of the best-estimated solution.

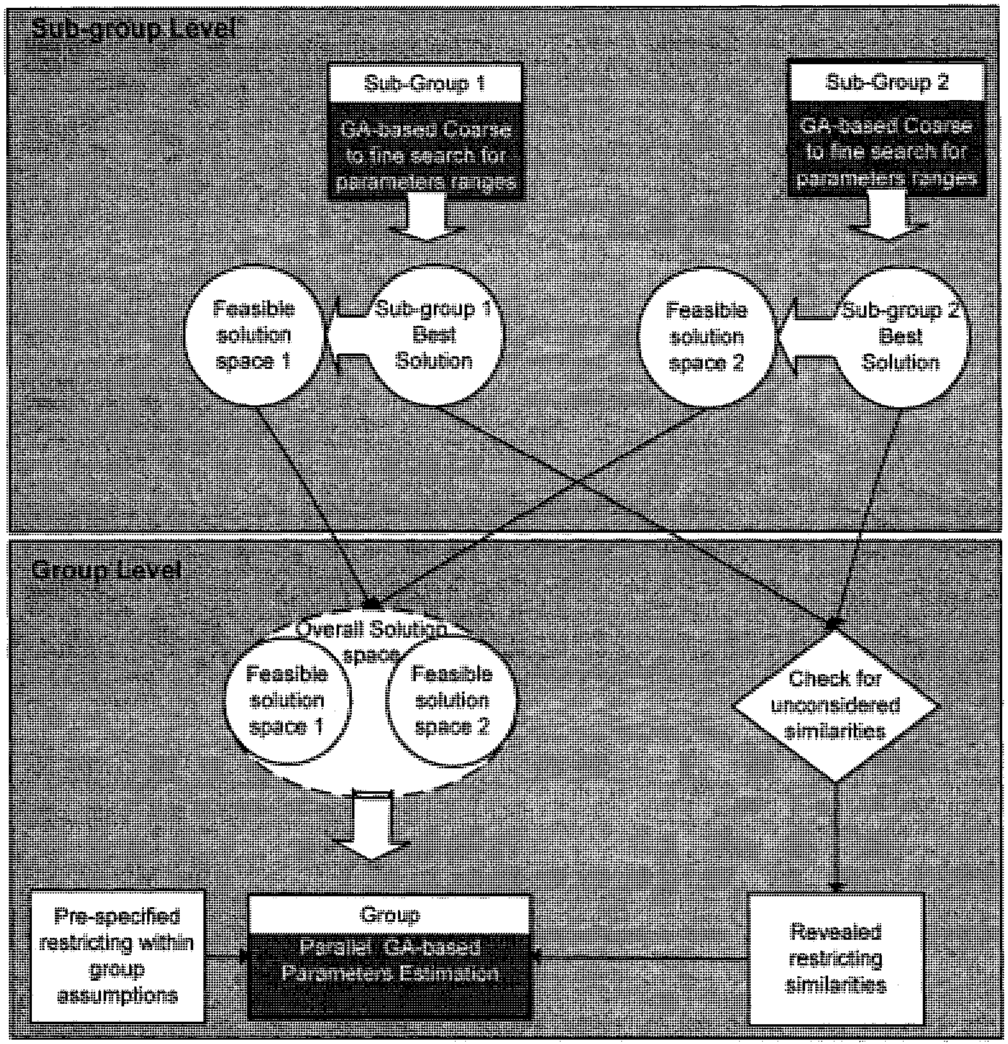


Figure 7.10 Multi-level Parameter Estimation Approach

2. *Group level parallel parameter estimation*

The group-level parameter estimation is concerned with the concurrent estimation of sub-group decision parameters within a combined search space. To achieve this simultaneous estimation, the GA estimator runs in parallel for both sub-groups. A parallel run is achieved based on the following criteria.

- A unified population; each solution point includes values of decision parameters for both sub-groups.
- Parallel simulations; estimation of predicted observations is performed through the simulation of the underlying deliberation process. This is performed for each sub-group, based on its respective parameters in the solution under consideration.

Outcomes of this step are a set of predicted observations for each sub-group, under each information scenario.

- Overall evaluation; a unified MAPE is estimated for each solution under investigation. The overall MAPE is the average of both sub-group MAPEs, weighted by the number of experiments observed for each sub-group.

Within the parallel estimation procedure, the increased dimension of the problem solution space challenges the efficient search for a near-optimal solution. Imposing reasonable restrictions on the problem-solution space is necessary. Restrictions are reasoned from two perspectives: number of parameters to be estimated and boundaries of each parameter value.

First, with respect to the number of parameters to be estimated, the pre-specified within-group assumptions, discussed in section 7.4.2.2, initially impose some restricting similarities between some of the group parameters. However, to investigate a further reduction in the number of unique parameters, a comparison is performed between the best solutions estimated for both sub-groups, through the sub-group estimation level. Other than the pre-assumed similarities, if the values of a certain parameter are estimated to be the same (within 10%) for both sub-groups, the two parameters are assumed to be one, and hence, reducing the number of total parameters.

The second perspective in limiting the problem solution space is concerned with the solution space boundaries. The performance of the parallel GA estimator relies on the localization of the solution space. As such, the boundaries of the group-level solution space are restricted to the envelope of the feasible solution spaces of the sub-group estimation level.

7.4.4.2 Between Deliberation Models Dimension

Until this point, each deliberation model is handled independently (i.e. different models for PN, ED, and EP). Pre-assumed restricting similarities between the parameters of the different deliberation models is not yet addressed. The parallel estimation procedure is limited to the sub-groups of each deliberation model. Extending this parallel estimation procedure to account for the similarities between deliberation models is computationally challenging. The computational complexity of such a problem is beyond the scope of our analysis. However, a step-wise estimation approach is adopted to account for the deliberation models' restricting similarities. In the step-wise approach, parameters with assumed similar values are transferred from one deliberation model to the other. It is important to note that the adopted approach is applied to both gender groups independently. No similarities are pre-assumed between gender groups.

The first step in the step-wise estimation procedure is concerned with the estimation of the ED-model parameters. The selection of this model as a starting point is based on the availability of observed measures for a number of respective information scenarios (4 descriptive information scenarios, compared to 2 prescriptive and 1 no information). The increased number of situational scenarios adds to the credibility of estimated results. Through the multilevel estimation approach, model parameters are estimated for ED-model (step 1). Values of common parameters (same color shade in Figure 7.7) are then transferred to EP-model, where a multilevel estimation procedure is to be performed (step 2). It is important to emphasize that the values of the transferable parameters are fixed to their pre-estimated values (in step 1) throughout the two levels of estimation of EP-model parameters (step 2). Finally, the third step is concerned with PN-model. After fixing pre-estimated parameters from the other deliberation models, the rest of the model's unique parameters are estimated. Only a group estimation level is conducted for the PN-model, as information reliability sub-divisions are irrelevant in a "no information" scenario.

To further reduce the number of parameters to be estimated in steps 2 and 3, an investigation of revealed similarities is undertaken. Revealed parameter matches are identified within each deliberation model as well as between deliberation models. Parameter values obtained at the sub-group estimation level for each step are compared to the estimated results at the previous step(s). Parameters with values within 10% of each other are unified as discussed next.

7.5 PARAMETER ESTIMATION RESULTS

7.5.1 Revealed Restricting Similarities

The following similarities between parameter sets are revealed during the estimation procedure. The parameters that are found similar (values within 10%) are unified into one parameter. Figure 7.11 presents the sequential flow of parameters from one step to the other, based on both pre-assumed and revealed results.

- Initial preference strength difference (ΔP) of ED-model and EP-model are similar, for both information reliability sub-groups.
- Attribute attention probabilities (π_{TT}, π_D, π_F, and π_C), under EP-model, are similar for both information reliability sub-groups.

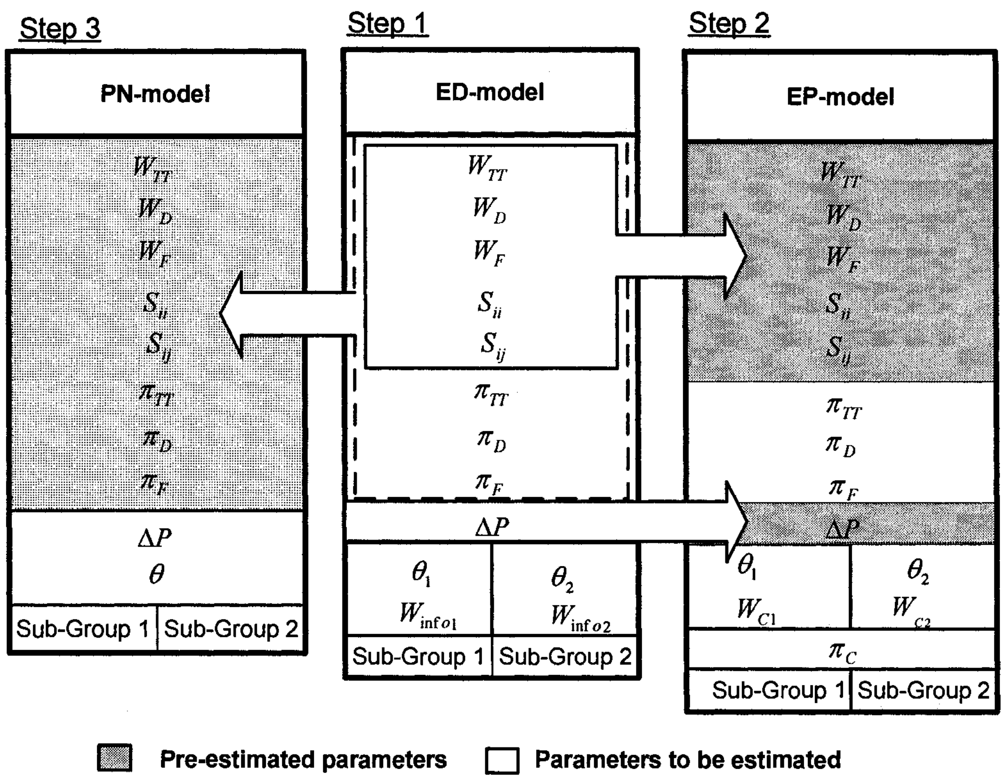


Figure 7.11 Step-wise Flow of Parameters Based on Pre-specified and Revealed Restricting Similarities

7.5.2 Estimated DFT Route Choice Model Parameters

Estimation of the deliberation models' parameters is conducted based on the above adopted methodology. General assumptions, pre-specified within group assumptions, and revealed restricting similarities are all considered during the course of estimation as detailed earlier. The developed GA-based optimization platform is used throughout the estimation procedure as the estimation tool. Based on extensive testing as well as common practices cited in the literature, the following GA variables are specified:

- Initial Population size= 500
- Cross-over rate= 0.7
- Mutation rate= 0.02
- Max number of generation= 400
- Convergence Threshold= 10%

For each model, parameter estimation is based on the minimization of MAPE of the predicted (from the model) versus the observed (from the mixed reality experiments) aggregated measures for the estimation data set. Figure 7.12 presents a sample of a GA run convergence chart.

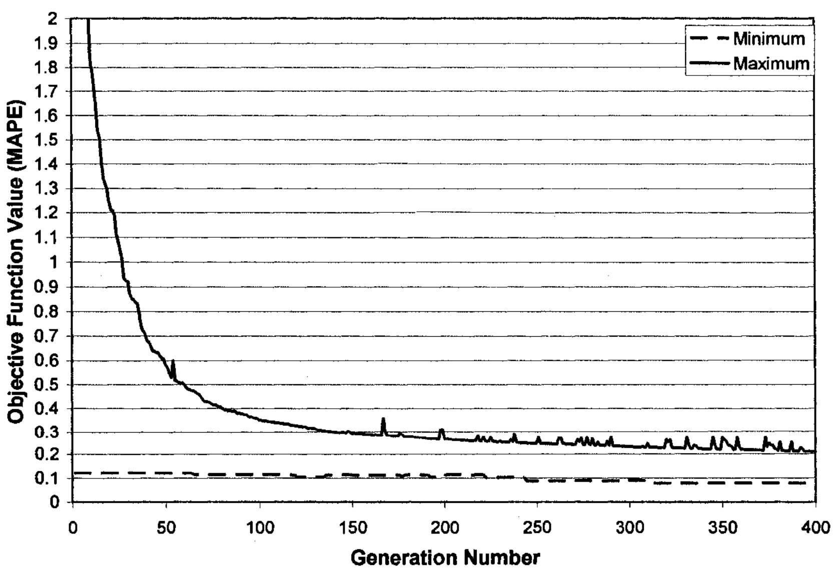


Figure 7.12 GA Convergence Chart

After completing the estimation process, MAPE is calculated for the test data set. The MAPE of the test data is used as an indicator of the performance adequacy of the estimated parameters. Table 7.7 presents the estimated models' parameter values for all data groups together with the calculated MAPEs for both estimation and testing data sets. Details of observed versus predicted measures for each deliberation model of each gender group are presented in Appendix C.

Table 7.7 Parameters Estimation Results

Model Parameters	Males					Females				
	ED-model		EP-model			ED-model		EP-model		
	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	PN-model	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	PN-model
W_{TT}	-9.05	-9.05	-9.05	-9.05	-9.05	-11.02	-11.02	-11.02	-11.02	-11.02
W_D	-5.67	-5.67	-5.67	-5.67	-5.67	-5.78	-5.78	-5.78	-5.78	-5.78
W_F	2.45	2.45	2.45	2.45	2.45	0.7	0.7	0.7	0.7	0.7
W_C	NA	NA	0.79	1.12	NA	NA	NA	4.78	9.23	NA
S_{ii}	0.65	0.65	0.65	0.65	0.65	0.69	0.69	0.69	0.69	0.69
S_{ij}	-0.3	-0.3	-0.3	-0.3	-0.3	-0.18	-0.18	-0.18	-0.18	-0.18
π_{TT}	0.71	0.71	0.42	0.42	0.71	0.76	0.76	0.5	0.5	0.76
π_D	0.14	0.14	0.03	0.03	0.14	0.14	0.14	0.06	0.06	0.14
π_F	0.15	0.15	0.07	0.07	0.15	0.09	0.09	0.06	0.06	0.09
π_C	NA	NA	0.48	0.48	NA	NA	NA	0.38	0.38	NA
W_{info}	0.23	0.45	NA	NA	NA	0.37	0.42	NA	NA	NA
ΔP	2.71	2.71	2.71	2.71	2.13	1.88	1.88	1.88	1.88	0.48
θ	14.2	23.67	12.33	15.38	5.55	12.55	21.94	8.22	19.49	5.75
MAPE (estimation)	7.40%		10.45%		0.03%	7.80%		5.20%		1.30%
MAPE (test)	22.90%		14.60%		19.90%	---	22.50%	---	25%	6.90%

Pre-specified restricting similarities
Revealed restricting similarities

7.5.3 Insights into Parameter Estimation Results

7.5.3.1 Within-Group Insights

The following is a discussion of revealed within-group variations in estimated parameter values. The objective is to enhance our understanding of the characteristics of the deliberation processes underlying route choice decisions. The representations of situational factors within the deliberation process parameters are the focus of this analysis. While estimated parameter values for the two gender groups are different, the general trends for the within-group variations are revealed to be similar. Thus, a unified discussion is presented.

1. *Attribute Weights*

- Estimated attribute weights have logical signs. Travel time and travel distance exert negative impacts as travellers logically prefer faster and shorter routes. Compliance attribute exerts a positive impact (0.79, and 1.12 for male sub-groups, 4.78, and 9.38 for female subgroups). Expectations for the freeway usage attribute are not well established; some drivers might favour taking the freeway while others may alternatively prefer the surface street. The aggregate perception within our conducted parameter estimation reveals a preference to take the freeway (a positive freeway usage weight; 2.45 for males and 0.7 for females). The increased preference to use the freeway coincides with the stated preference questionnaire results, discussed in section 5.2.
- The travel time attribute payoff is the most significantly perceived one (with the highest attribute weight).
- The impact of information reliability level is quite clear in altering the compliance weight (W_C). As information reliability increases, the confidence in provided recommendations increases and so does the weight allocated to the compliance attribute.

2. *Feedback Matrix*

- The self-connection (S_{ii}) values are estimated to be sub-unity (0.65 for males, and 0.69 for females). This means that even though the deliberation time frame is limited, there is a decaying effect of instantaneous preferences with time. Nonetheless, the decaying rate is limited.
- Estimated negative values for the inter-connection (S_{ij}) elements of the feedback matrix reveal the competitive nature between choice alternatives (-0.3 for males, and -0.18 for females).

3. *Attribute Attention Probabilities*

- In the absence of specific prescriptive guidance, travel time is significantly the most salient attribute of all. This is reflected in an attention allocation probability of 0.71 compared to 0.14 and 0.15 for travel distance and freeway usage respectively, for the male ED-model as an example. The estimated order of significance of attributes, based on attention allocation probabilities, coincides with the stated preference questionnaire results. However, the precedence of the travel time attribute is much more pronounced in revealed observations.
- In the presence of en-route prescriptive information, the compliance attribute appears in the picture taking over a significant portion of the decision-maker's attention. The attention allocation is almost divided between travel time (0.42 for males, and 0.5 for females) and compliance (0.48 for males, and 0.38 for females), leaving minimal consideration to other attributes.
- Within EP-model, attribute attention probabilities are estimated to be equal for both information reliability sub-groups (revealed restricting similarities). This means that the impact of information reliability on drivers' compliance is manifested only in the value of the compliance weight. However, compliance attention probabilities are not affected.

4. *Information Weight*

- A variation in the information weights of ED-model is revealed with the change in information reliability level (for example from 0.23 to 0.45 for males). The higher the information reliability level, the larger its influence on drivers' perceptions.

5. *Initial Preference Difference*

- Initial preference differences for both en-route deliberation models, for both sub-groups, are revealed to be similar (2.71 for males, and 1.88 for females). This means that decision-makers' en-route initial bias is formulated based on past experiences, with no specific impacts of disseminated information characteristics.
- The estimated en-route initial preference difference is higher in magnitude than the pre-trip one (2.71 vs. 2.13 for males and 1.88 vs. 0.48 for females). This could be related to the "inertia effect;" where the en-route pre-deliberation bias to continue on the chosen route exceeds the pre- trip one.

6. *Threshold Bound*

- The impact of information characteristics in altering estimated threshold bounds is significant. Figure 7.13 and Figure 7.14 display the variations in threshold bounds for different deliberation models for male and female groups, respectively. While both en-route deliberation processes start from the same level of initial bias, their decision-making thresholds are substantially different. The ED-model is observed to have higher estimated threshold bounds compared to the EP-model. Explicit guidance advice is perceived to be less mentally demanding. In addition, information reliability is another dimension that has a direct impact on threshold bounds. Higher reliability levels stimulate more serious/cautious deliberation processes and hence increased threshold bounds.
- The estimated threshold bound for PN-model is considerably lower than the en-route ones. This trend reveals two insights:

- In the absence of information, during recurrent trips, drivers do not undertake a long deliberation process prior to starting each trip. This could be related to the default choice type behaviour in route choice literature (Lotan, T. and Koutsopoulos, 1999). The default choice behaviour is simply the inclination to make the same choice, each time, in the absence of conflicting information.
- The choice context has a direct impact on the deliberation processes. During en-route choice decisions with VMS descriptive or prescriptive information provision, drivers are triggered to think for sometime prior to reaching the decision node. However, in pre-trip decisions with no information, drivers start their trip and do not waste time undergoing a long deliberation process with uncertain outcomes, as there is no new information to think about.

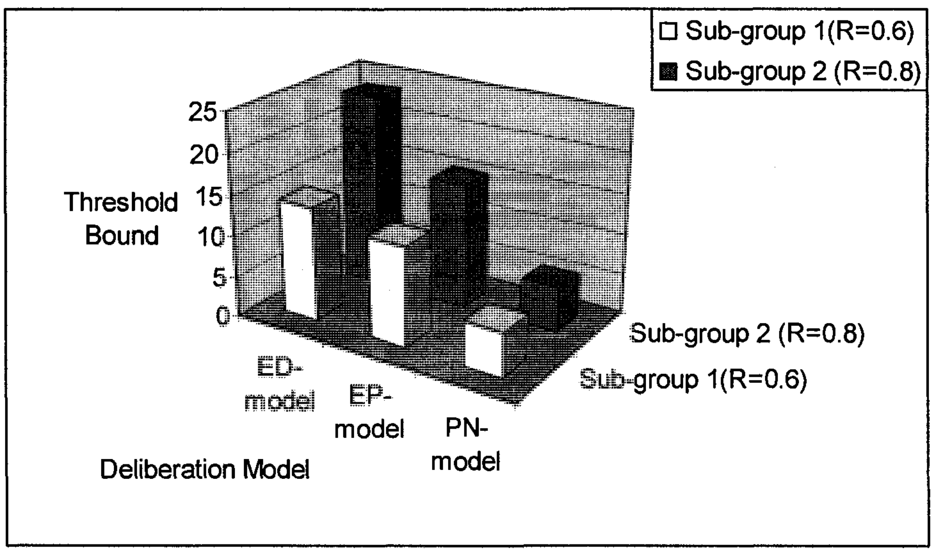


Figure 7.13 Estimated Threshold Bounds for the Male Group

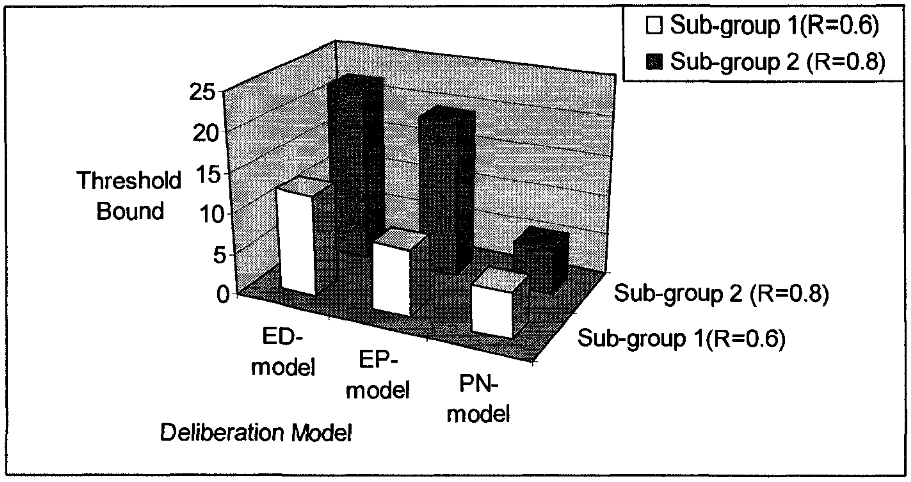


Figure 7.14 Estimated Threshold Bounds for the Female Group

7.5.3.2 Between-Group Insights

While the general variation *trends* in estimated parameters values within each gender group are estimated to be similar, the estimated values of corresponding parameters and variations levels are different. In this section, parameter values and variation levels are discussed for the two gender groups, from a comparative perspective.

1. *<u>Attribute Weights</u>*

Estimated weights for travel time, and compliance attributes for the female group are significantly higher than their corresponding values for the male group (Figure 7.15). The higher values reflect an amplified influence of travel time gains and information source recommendations on females' route choice decision-making process. Alternatively, a lower value of the freeway usage attribute weight is estimated for the female group. A reduced impact of freeway usage consideration is, hence, revealed.

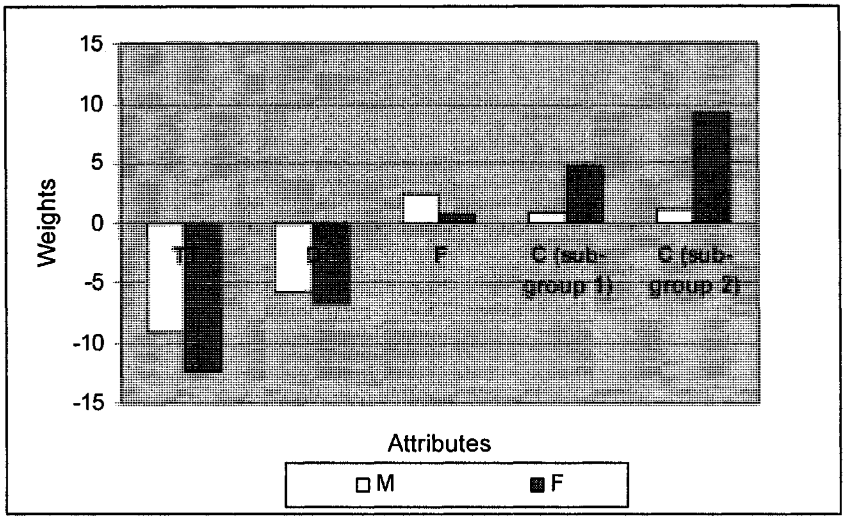


Figure 7.15 Estimated Attributes Weights

2. *Feedback Matrix*

Comparable values are estimated for the self-connection (S_{ii}) (0.65, and 0.69 for males and females respectively). However, the competitiveness between alternatives is more pronounced within the male group. This is represented by the higher value of interconnection (S_{ij}).

3. *Attribute Attention Probabilities*

In general, reasonably comparable values are estimated for all attribute attention probabilities for the male and the female groups. However, a slight decrease in the attention probability allocated to the freeway usage attribute is estimated for the female group.

4. *Information Weights*

While descriptive information consideration increases as information reliability level increases for both gender groups, the magnitude of the increase in W_{info} is different. Estimated W_{info} values, for the male group, reveal an increased sensitivity to the reliability of disseminated descriptive information, compared to the females (Figure 7.16). Males tend to lose confidence in disseminated information more vigorously.

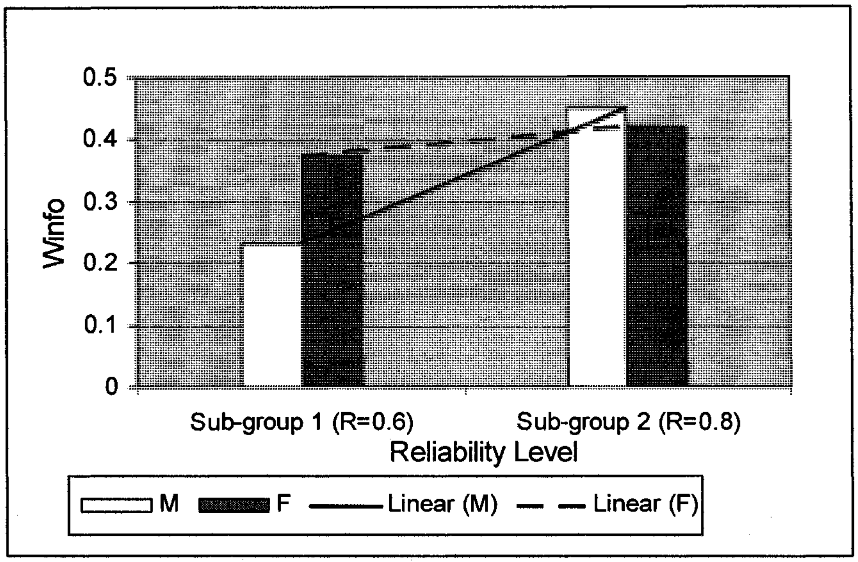


Figure 7.16 Estimated Information Weights

5. *Initial Preference Difference*

An increased level of initial bias is estimated for the male group for both pre-trip and en-route deliberation models. However, the estimated sensitivity of ΔP to the choice context is more pronounced in the female group (Figure 7.17). A considerable increase in the level of initial preference difference is revealed for the female group in en-route deliberation models, compared to the pre-trip one.

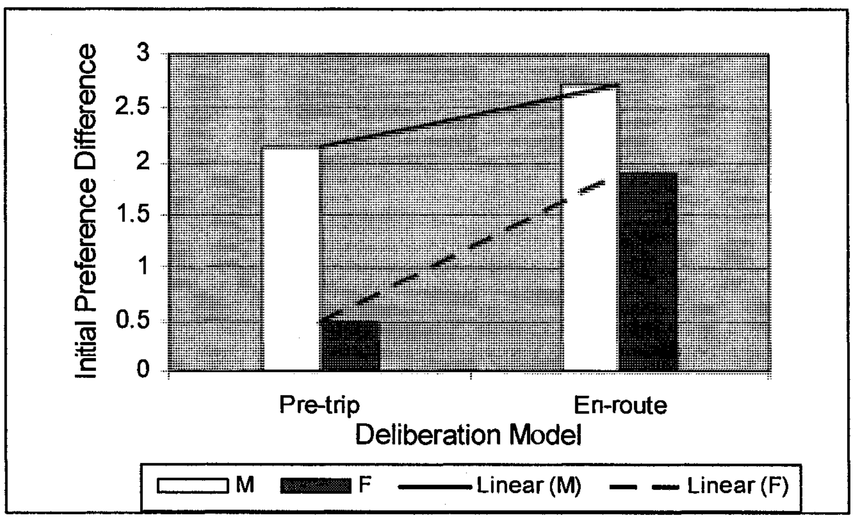


Figure 7.17 Estimated Initial Preference Differences

6. *Threshold Bound)*

Estimated values of threshold bounds vary from males to females in multiple dimensions. In an attempt to gain insight into the variation trend, estimated threshold values for each deliberation model are compared separately.

- In the ED-model, a slight decrease in the value of θ could be depicted for both sub-groups of the female group (Figure 7.18). Nonetheless, the sensitivity to information reliability level is similar for both gender groups.
- In the EP-model, a more pronounced sensitivity to information reliability is estimated for the female group (Figure 7.19). A lower value of θ for sub-group 1 and a higher value for sub-group 2 magnify the difference.
- Finally for the PN-model, the estimated value of θ for the female group is higher than the male one. This reflects a more cautious behaviour in habitual choice situations with no information provision.

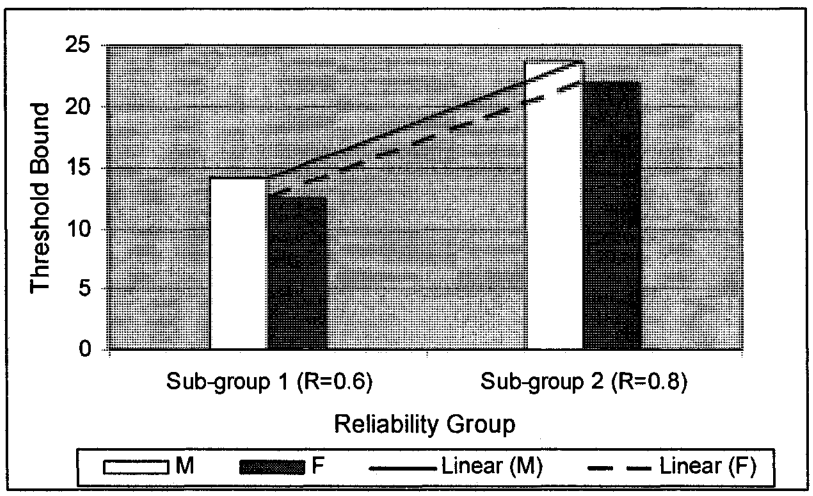


Figure 7.18 Estimated Threshold Bounds for ED-model

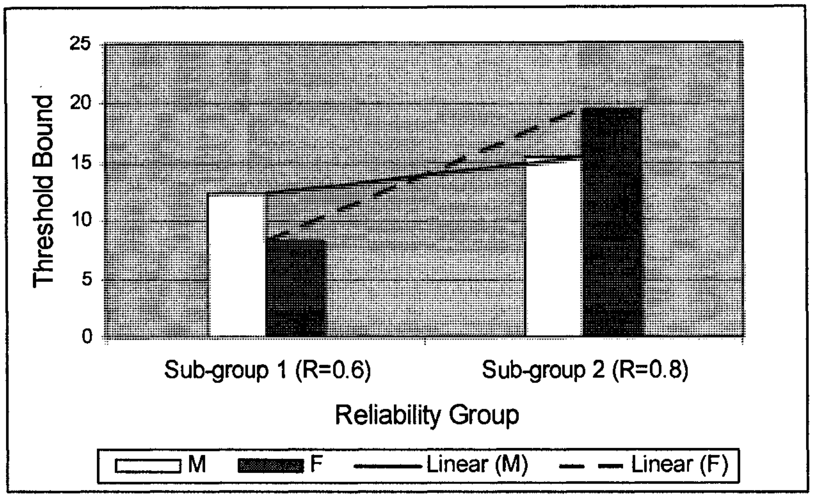


Figure 7.19 Estimated Threshold Bounds for EP-model

7.6 SUMMARY OF MAIN FINDINGS

Estimation of DFT route choice model parameters is conducted using a multilevel step-wise GA-based estimation procedure. Parameter estimation is based on the minimization of the differences between predicted and observed choice measures. Observed data are categorized into a number of data sets. Aggregate choice percentages and MDTs are estimated for each data set, under different information scenarios. Predicted measures are obtained through repeated computer-based simulations of each deliberation situation using the DFT model. Parameter estimation results report a MAPE ranging from 0.03% to around 10%, for the estimation data. An increased MAPE is estimated from the test data set, ranging from around 7% to 25%. It is noteworthy that the small sample size of the test data may have contributed to the larger errors ranges. Nevertheless, results from both the estimation and testing data sets are very encouraging. These positive results from the DFT model and the diversity of insights it offers certainly warrant further future experimentation and further testing. In the following, a brief recap of the main findings is presented.

Consistent with the literature and intuitive expectations, the trade-off between alternative routes is mostly based on travel time savings. The role of travel distance and freeway usage attributes is less influential. While estimated attribute attention probabilities, for both gender groups, are almost similar, a considerable variation is observed in estimated attribute weights. Except for the freeway usage attribute, lower values of attribute weights are estimated for the male group.

Neither information form nor its reliability level impacts the value of the en-route initial preference bias. However, different values are estimated for each gender group. A lower level of bias is estimated for the female group. As such, the level of initial bias is revealed to be dependent on the decision-makers' accumulated experiences with no information influence.

The impacts of information reliability level within ED-models are manifested in the values of two parameters: information weight and threshold bound. As information reliability increases the information weight increases. A similar trend is estimated for the threshold bound. As the information reliability level increases, decision-makers perceive the deliberation process more seriously by increasing their threshold bounds. The level of impact of the variation in information reliability on estimated threshold bounds is revealed to be similar for both gender groups. However, an increased level of impact is estimated for the male group with respect to the information weight.

On the other hand, within EP-models, the impacts of information reliability levels are limited to the compliance weight and the threshold bound. No impact is estimated on the attribute attention probabilities, including the compliance one. An increase in the values of both impacted parameters is estimated with the increase in the reliability of disseminated information. An increased level of impact is estimated for the female group for both parameters. This reflects that, in the presence of specific advice, females exhibit an increased sensitivity to the reliability of disseminated information.

Finally, the impact of the deliberation environment in varying deliberation model parameters is clearly observed in the different values of estimated threshold bounds. Within the en-route choice context, increased threshold bounds values are estimated for ED-models compared to EP-models. This indicates that the deliberation processes under descriptive information provision are perceived to be more challenging. On the other hand, estimated threshold bounds for PN-models are considerably less than en-route ones. This decrease could be interpreted in two dimensions. First, habitual choice attitude is common in recurrent trips. This attitude is increasingly manifested in the absence of information. Second, in the pre-trip deliberation context, travellers seem to start their trip with little deliberation. While en-route, with information provision, traveller consume time deliberating the pros and cons of alternatives.

8 SENSITIVITY ANALYSIS OF ROUTE CHOICE TO DELIBERATION DYNAMICS

8.1 PRÉCIS

One of the main motivations for adopting DFT as a theoretical framework for modelling drivers' route choice behaviour is its ability to capture the dynamics of the choice process. The direct impact of the deliberation time dimension on altering choice decisions is of significant importance in route choice modelling. Choice decisions could be reversed under time pressure constraints. The time pressure constraint means that the available deliberation time frame is shorter than what the driver needs for making an unconstrained decision. Within DFT abstraction of the route choice deliberation process, drivers make their choices when their preference strength exceeds a threshold bound for a specific alternative. If the available deliberation time is less than what they need, the choice process is cut off with a premature decision prior to reaching that bound. The imposed interruption of the deliberation process could, therefore, result in different choice decisions.

The focus of this chapter is on analyzing the impact of the deliberation time dimension on choice decisions. Simulated time pressure constraints are imposed on drivers' en-route deliberation processes using the developed DFT model. The impact trend is subsequently analyzed. For comparison purposes, an alternative structural-oriented parameter estimation approach is investigated. Results of the structural-oriented estimation approach are compared to the process-oriented DFT approach. Conclusions on the significance of the added value of a process-oriented modelling approach are, finally, discussed.

8.2 SIMULATED TIME PRESSURE CONSTRAINT

The impact of time pressure constraints is quite evident in en-route choice decisions. The en-route deliberation process is restricted to the available time frame prior to the divergence point. Traffic information could be disseminated to drivers through different technologies. Some of which, such as radio reports, could reach a driver just before the diversion node. This results in much reduced deliberation time frames.

Therefore, the potential of various traffic communication technologies in disseminating useful and usable traffic information can significantly vary. As such, there is a need for enhancing our understanding of the impact of time pressure constraints on drivers' compliance behaviour.

Within the scope of our experimental analysis, traffic information is disseminated to subjects through a VMS. The location of the VMS is well before the divergence node, relaxing the time pressure to allow for a fully informed decision process. Accordingly, the full deliberation process is captured until the unconstrained thresholds are reached. In the calibrated DFT model, shorter deliberation times can be imposed and the impact of which can be assessed. In this section, simulated route choice data are used to assess drivers' compliance attitudes under time constraints.

8.2.1 Simulation Scope

Generation of route choice data under time pressure constraints is based on the simulation of the deliberation processes, in accordance with the developed DFT route choice model. This analysis utilizes estimated en-route decision parameters for the male group only. Choice percentages are estimated for two information scenarios: DHL and PLS. Each of the two scenarios represents a challenging situation, where disseminated information opposes drivers' intuitive biases to take the Gardiner Expressway. Different choice percentages are estimated for different information reliability sub-groups.

Simulation of the deliberation process is a second-by-second estimation of the evolution of drivers' preference strengths toward each of the alternative routes. In an un-constrained deliberation process, decisions are made based on the first preference strength exceeding the upper-threshold bound. Under a time pressure constraint, the deliberation process is limited to a specific deliberation frame. If a decision is not reached within the specified frame, the alternative with the highest preference strength, at the deliberation time limit, is chosen. Experimentally observed mean deliberation time frames range from 4.5 to 16 seconds. A time pressure of 3, 6, and 9 seconds are externally imposed to restrict the deliberation process. Choice percentages are based on 100 repeated simulations of the respective deliberation processes. Choice percentages of the base case (with no time pressure constraint) are preserved for comparison purposes.

8.2.2 Time Pressure Impact on Compliance Behaviour

Sub-group choice percentages are estimated for each information scenario, under each considered time frame. As the adopted information scenarios are both challenging (favouring the Lakeshore), compliance rates are estimated to be the Lakeshore choice percentages. Figures 8.1 and 8.2 present the estimated sub-groups' compliance rates, for the descriptive and prescriptive information scenarios.

A completely different behavioural trend is revealed under different information scenarios. Descriptive information provides drivers with network conditions (congestion levels) and it is up to the driver to make a decision. The incorporation of descriptive information into the decision-making process is, thus, time-consuming. Under tight time-pressure constraints, the degree of influence of disseminated information in route choice behaviour is less pronounced. Longer deliberation time frames allow for more elaborate deliberation processes. Under a higher perceived information reliability level, compliance rates increase with the relaxation of the time pressure constraint. As the information reliability level decreases, drivers' perception of the significance of provided descriptive information decreases. The reduced confidence in provided information discourages drivers from undertaking elaborate deliberation processes, regardless of the available time frame. Compliance rates are, therefore, lower in value and less influenced by time pressure levels under the reduced reliability level. The practical implication of this finding is that if travellers are not provided with sufficiently accurate information and sufficiently long time to deliberate it, they are less likely to comply. The DFT model captures and quantifies this trend as shown in Figure 8.1.

On the other hand, prescriptive information provides drivers with a route choice recommendation/decision rather than a plain description of the choice situation. Unlike descriptive information, perceived gains from prescriptive information isn't quite clear. An optimistic interpretation could assume that the provided recommendation is based on a substantial travel time gain. Alternatively, minimal travel time gains are also possible.

Under tight-time pressure constraint, drivers are more inclined to adopt the explicit advice, as there is no time for further deliberation. As the deliberation time frame increases, a more elaborate deliberation process that incorporates the consideration of all possible expectations of travel time gains and information reliability is undertaken, possibly magnifying uncertainty. As such, a decrease in compliance rates is estimated with increased deliberation time frames, for both information reliability sub-groups. Nonetheless, under reduced reliability, compliance rates are lower, in general, and the effect of time pressure constraints are less pronounced (significant only under extremely tight situations).

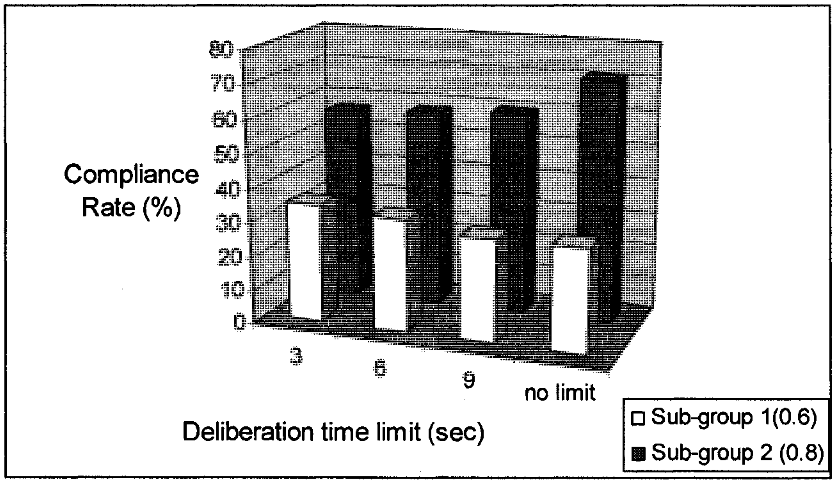


Figure 8.1 Compliance rates under DHL

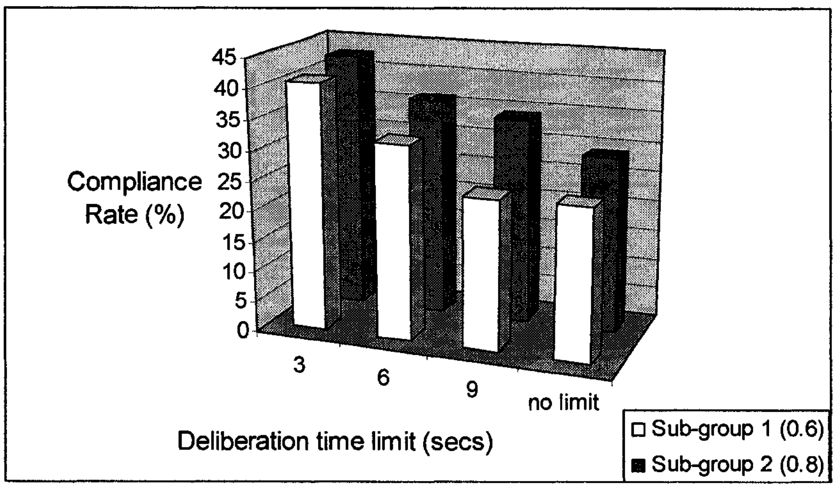


Figure 8.2 Compliance rates under PLS

8.3 STRUCTURAL-ORIENTED VS. PROCESS-ORIENTED PARAMETER ESTIMATION

Estimation of DFT route choice model parameters is based on the minimization of prediction errors. From a process-oriented modelling perspective, prediction errors are not solely concerned with choice decisions. They also include the time taken to reach this decision. Accordingly, MAPE, incorporating choice percentages and MDT, is an appropriate measure of prediction errors. As such, the developed DFT route choice model is realized as a process-oriented decision model, both conceptually (theoretical framework) and operationally (experimental-based calibration). In the process-oriented DFT model the cognitive/psychological mechanisms underlying the deliberation process are explicitly represented.

At this point of our research, a persistent conceptual question lingers; *how different would the results be if we adopt a structural-oriented modelling approach?* In a structural-oriented modelling approach, a relationship is to be formulated between the decision inputs and outputs with minimal consideration of the underlying deliberation process. In an attempt to answer the preceding question, we use the DFT model but a structural-oriented parameter estimation methodology in our investigation. While the same DFT route choice model conceptual framework is preserved, the time dimension is ignored during the parameter estimation process. Ignoring the time dimension during the estimation process focuses the model on the resulting choice percentage while disregarding the dynamics of the decision process, i.e. reduces the DFT model to a structural one. The following sections present the re-estimation details, results and significances.

8.3.1 Structural-oriented Re-estimation of the DFT Model Parameters

The re-estimation of the DFT model parameters is performed for the male group using a structural-oriented estimation methodology. The new estimation methodology is similar to the previous one in terms of estimation assumptions, restricting similarities, and estimation approaches. The developed GA-based estimator is also used in the re-estimation. However, the new estimation methodology primarily differs in its formulation of the prediction error. A modified formulation of MAPE is adopted, reducing the prediction measures to choice decisions only (Equations 8.1 and 8.2). As such, evaluation of the performance of the calibrated model is based only on its ability to accurately predict choice percentages under different information scenarios, without consideration of the MDTs.

$$Modified\_MAPE = \sum_{i=1}^{n} w_i * \left| \%G_{predicted}(i) - \%G_{observed}(i) \right| \tag{8.1}$$

$$w_i = \frac{N_i}{N_T} \tag{8.2}$$

Where:

- n, is the number of information scenarios of the deliberation model under investigation
- $\%G_{Predicted}(i)$, is the Gardiner predicted choice percentage under information scenario i.
- $\%G_{Observed}(i)$, is the Gardiner observed choice percentage under information scenario i.
- w_i, weight assigned to the estimation error of information scenario i.
- N_i, is the number of conducted in-lab simulated route choice experiments under information scenario i, from which observed measures are estimated.
- N_T, total number of conducted in-lab simulated route choice experiments for the deliberation model under investigation.

In re-estimating the model, (1) estimated values for the feedback matrix parameters are preserved from the process-oriented estimation results, and (2) revealed restricting similarities from the process-oriented estimation results are also preserved. Table 8.1 presents the values of the re-estimated parameters together with their original values (process-oriented results). Table 8.2 presents the MAPEs for the estimation and the testing data sets, from both estimation approaches. While the structural-oriented estimation approach is based on the Modified-MAPE, the original MAPE is the real indicator of the model prediction capabilities. Details of observed versus predicted measures for each deliberation model of the male group, under the structural-oriented estimation approach, are presented in appendix C.

Table 8.1 Structural-oriented vs Process-oriented DFT Route Choice Model Decision Parameters

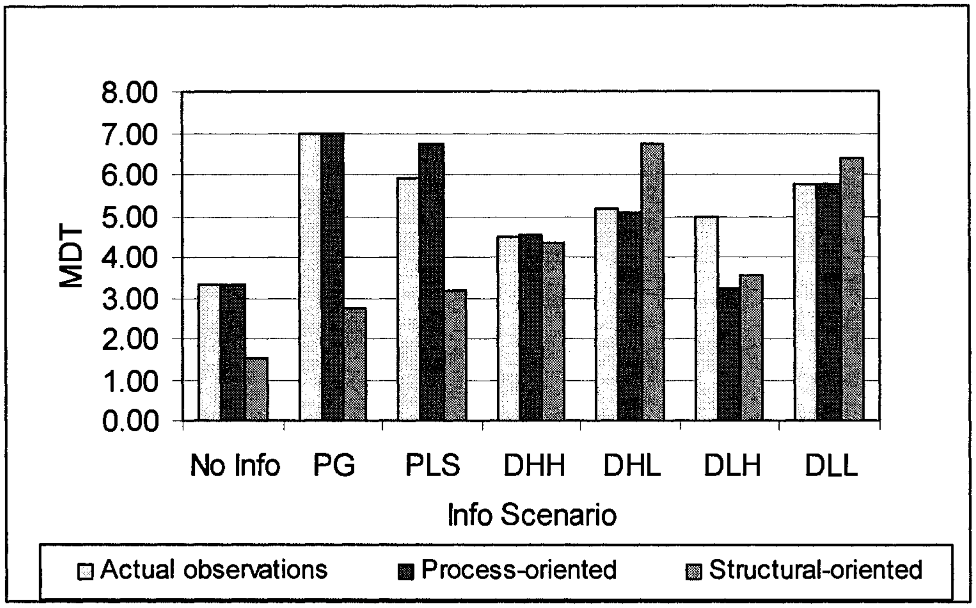
Model Parameters	Structural-oriented Parameter Estimation					Process-oriented Parameter Estimation				
	ED-model		EP-model			ED-model		EP-model		
	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	PN-model	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	Sub-group 1 (R=0.6)	Sub-group 2 (R=0.8)	PN-model
W_T	-13.31	-13.31	-13.31	-13.31	-13.31	-9.05	-9.05	-9.05	-9.05	-9.05
W_D	-16.57	-16.57	-16.57	-16.57	-16.57	-5.67	-5.67	-5.67	-5.67	-5.67
W_F	6.61	6.61	6.61	6.61	6.61	2.45	2.45	2.45	2.45	2.45
W_C	NA	NA	5.28	9.53	NA	NA	NA	0.79	1.12	NA
S_{ii}	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65
S_{ij}	-0.30	-0.30	-0.30	-0.30	-0.30	-0.3	-0.3	-0.3	-0.3	-0.3
π_{TT}	0.65	0.65	0.36	0.36	0.65	0.71	0.71	0.42	0.42	0.71
π_D	0.14	0.14	0.03	0.03	0.14	0.14	0.14	0.03	0.03	0.14
π_F	0.21	0.21	0.11	0.11	0.21	0.15	0.15	0.07	0.07	0.15
π_C	NA	NA	0.51	0.51	NA	NA	NA	0.48	0.48	NA
W_{info}	0.41	0.81	NA	NA	NA	0.23	0.45	NA	NA	NA
ΔP	2.83	2.83	2.83	2.83	2.36	2.71	2.71	2.71	2.71	2.13
θ	22.15	5.75	12.68	17.52	3.70	14.2	23.67	12.33	15.38431	5.55

Table 8.2 Structural-oriented vs Process-oriented MAPEs

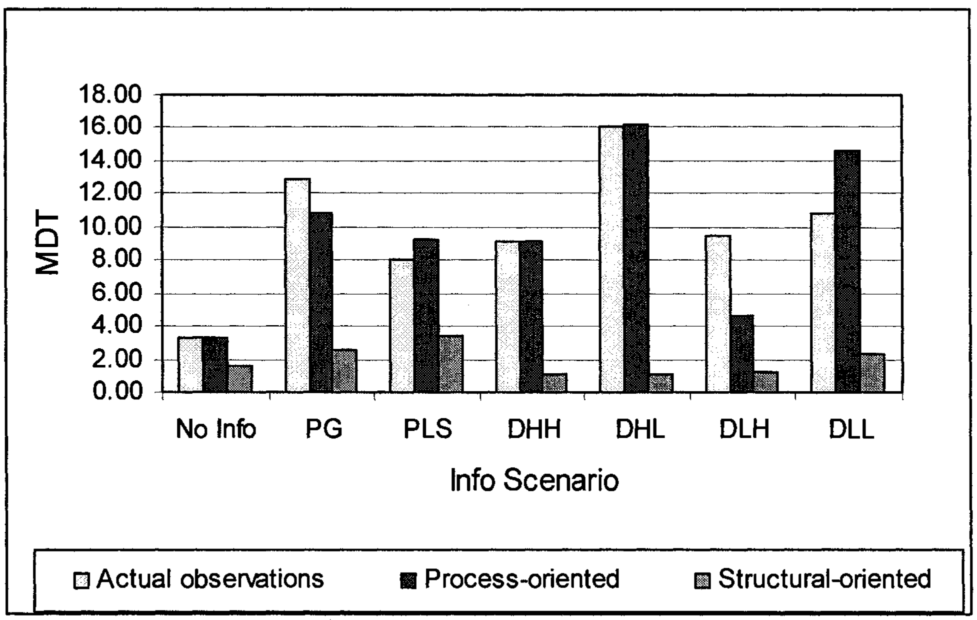
Deliberation Model	Structural-oriented Estimation				Process-oriented	
	Modified-MAPE (without MDT)		Original MAPE (with MDT)		Original MAPE (with MDT)	
	Estimation	Test	Estimation	Test	Estimation	Test
ED	0.02%	12.10%	23.60%	25.30%	7.40%	22.90%
EP	0.01%	7.10%	32.70%	35.2	10.45%	14.60%
PN	0.00%	9.50%	23.00%	27.00%	0.03%	19.90%

Re-estimation results reveal considerable differences in estimated parameter values as well as performance indicators. The performance of the structural model, based on the modified MAPE without MDT, is misleadingly superior to the process oriented one. Substantially low values of the Modified-MAPEs are estimated ranging from 0 to 0.02%. Reasonably low testing error values are also estimated for the Modified-MAPE, ranging from 7 to 12%. However, if the structural model is evaluated based on errors in predicting both choice percentages and deliberation times, the performance substantially deteriorates, well below the performance of the process model. This clearly indicates that while the structural model can more accurately "fit" choice percentages, it is challenged to capture the underlying behavioural process. The elimination of the MDT from the error function seems to have simplified fitting the model to the choice percentage data. The importance of capturing the behavioural deliberation process has been qualitatively and quantitatively demonstrated in the previous chapters and hence cannot and should not be ignored.

Figure 8.3 further illustrates the incapability of the structural model to capture the deliberation process and MDT. The major inconsistencies between predicted and observed deliberation time frames using the structural model reveal a reduced credibility in predicting the deliberation process. Predicted deliberation time frames are, in most cases, significantly lower than actual observations. For sub-group 2, unrealistically small deliberation time frames of less than 2 seconds are estimated for many choice situations. In another words, the model is able to predict correct choice decisions for the data set in hand but for the wrong reasons, possibly assuming infinite mental processing capabilities of the drivers. As such, the generalization of this type of model could result in mis-predictions. The potential gains of adopting a process-oriented estimation approach are, accordingly, revealed. Further insights into the differences between estimated parameter values using both estimation approaches, and their implications, are discussed in the following section.



a) Sub-group 1 (R=0.6)



b) Sub-group 2 (R=0.8)

Figure 8.3 Estimated Vs Actual MDTs

8.3.2 Comparison of Structural-oriented vs. Process-oriented Model Parameters

Prediction of drivers' route choice decisions is one of the main objectives of developing route choice models. However, the contribution of estimated parameters values is not limited to reproducing choice percentages in a black-box manner. Enhancing our understanding of the role of different actors in the deliberation *process* is of equivalent importance, if not more important. The representation of different situational/personal factors and the sensitivity of the deliberation process to changes in the choice environment are all captured through the estimated values of the model parameter. Thus, differences in estimated parameter values don't only mean different choice predictions but also different implications. As such, the level of impact of the estimation approach on parameter values is investigated in this section. Only pronounced variations are discussed.

1. *Attribute Weights*

A general increase in attribute weights is depicted under the structural-oriented estimation approach (Figure 8.4). The increase in attribute weights reflect a tendency to make near- instantaneous choice decisions. Lower attribute weights allow for a smoother evolution of preference strengths, and hence, a more elaborate deliberation process. A trend variation is depicted. While the travel time weight is the highest in magnitude under the process-oriented estimation approach, travel distance takes over in the structural-oriented approach, which is not only counter-intuitive but also contradicts the stated preferences of the test subjects. Moreover, an increased sensitivity of the compliance weight to different levels of information reliability is depicted under the structural-oriented estimation approach.

2. *Information Weight*

An increased influence of descriptive information on drivers' perceptions of anticipated congestion states is depicted under the structural-oriented estimation approach. Figure 8.5 displays the estimated differences in information weights. A substantial increase in W_{info}, to almost double its original value, is depicted. The increased differences between estimated sub-group values, reflects an increased sensitivity to information reliability.

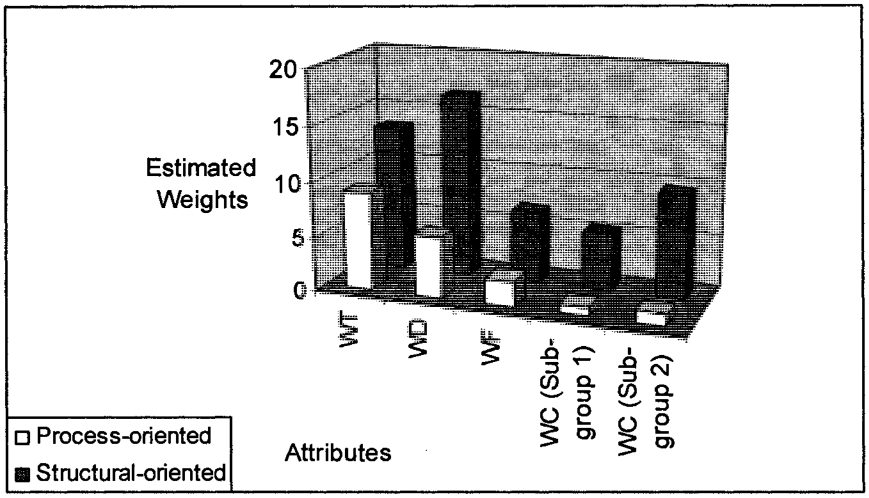


Figure 8.4 Structural-oriented vs Process-oriented Attributes Weights

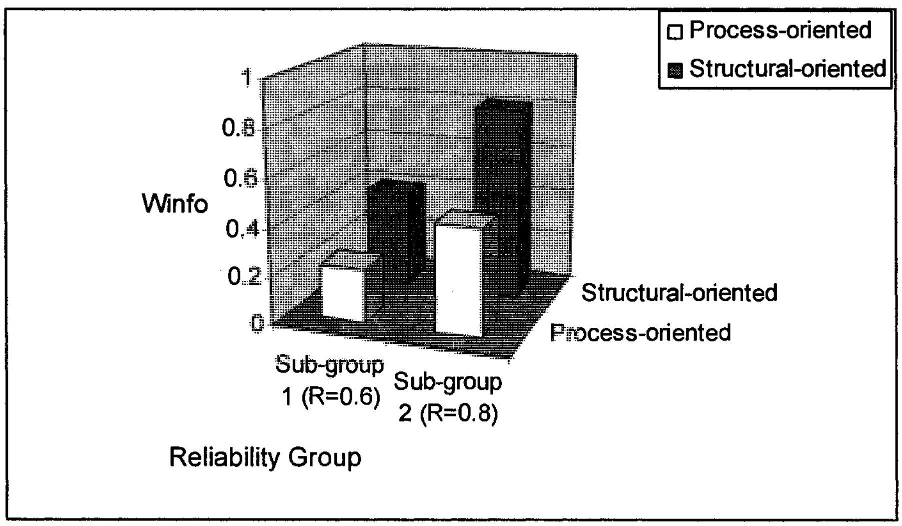
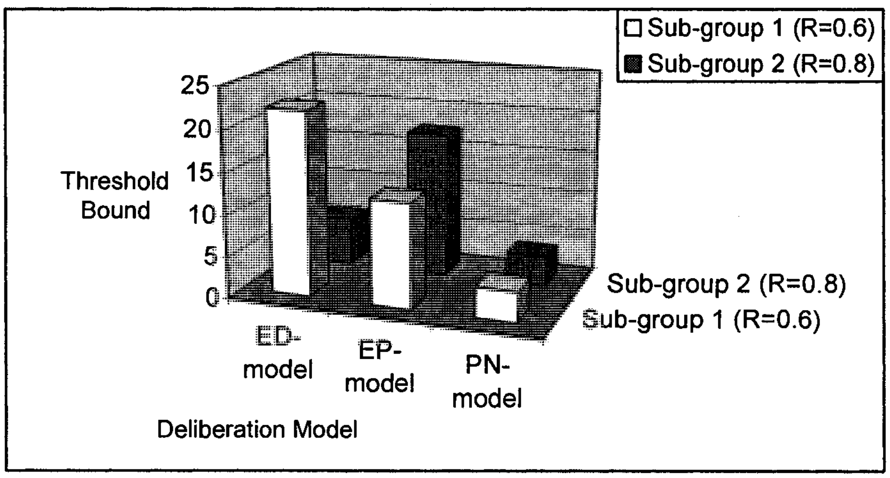


Figure 8.5 Structural-oriented vs Process-oriented Information Weights

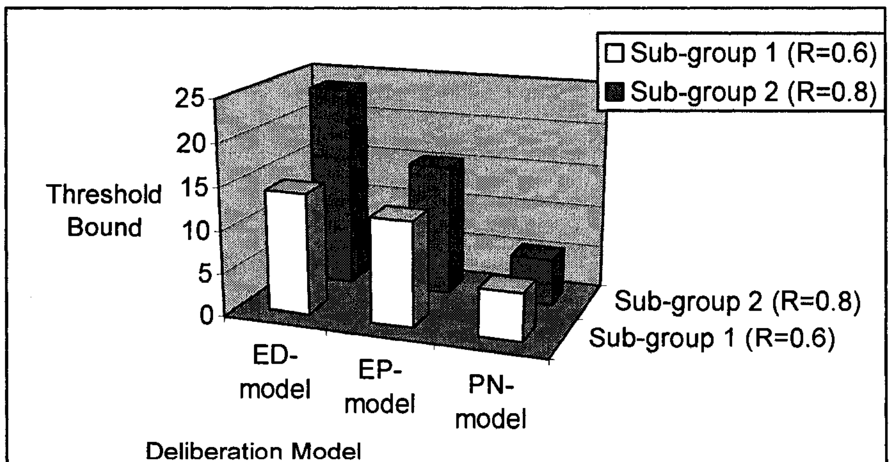
3. <u>Threshold Bound</u>

A substantially different impact trend of information characteristics on threshold bounds is revealed under the two estimation approaches (Figure 8.6). Under the process-oriented estimation approach, increased information reliability levels result in increased threshold bounds. In addition, descriptive information provision requires a higher threshold bound than prescriptive one. Moreover, higher threshold bounds are estimated for en-route informed deliberation models compared to the no information pre-trip one.

A completely different impact trend is revealed under the structural-oriented estimation approach. A reversed trend is estimated for the impact of information reliability on ED-model threshold bounds; a lower value of θ is estimated for the higher reliability level sub-group. In addition, the impact of information form (descriptive vs prescriptive), for sub-group 2, is also reversed.



a) Structural-oriented Estimation Approach



b)Process-oriented Estimation Approach

Figure 8.6 Structural-oriented vs Process-oriented Threshold Bounds

8.4 THE PROCESS-ORIENTED MODELLING APPROACH: IS IT WORTH THE EFFORT?

The debate between advocates of structural-oriented and process-oriented modelling approaches of the decision-making process has long been argued in the route choice literature (Polak, 1998). While the structural approach is more tractable and easily implemented, it is myopic as it fails to account for the behavioural deliberation process itself. It is hence, vulnerable to mis-predictions. On the other hand, the process approach offers a descriptive mechanism of the cognitive process underlying drivers' choice decisions. As such, it could theoretically be regarded as an ideal approach of modelling choice decisions. However, as this approach delves into perceptual and cognitive processes, testing and calibrating these types of models are realized to be a profound undertaking.

This research is motivated by the potential usefulness of the process-oriented modelling approach of drivers' route choice decision-making process. The uncertainties in the choice environment together with the dynamic nature of the deliberation process inspired the adoption of the DFT as the route choice model theoretical background. Estimation of model parameters is achieved through data collected from laboratory-simulated route choice experiments in an enhanced mixed-reality environment. The mixed reality simulation platform is designed, especially, for that purpose. Still, extensive experimentation, with a large cross-sectional-type sample of drivers, under different experimental controls, is necessary for the development of a full-fledged version of the DFT route choice model. Prior to undertaking this further research step, an assessment of the added-value of the developed process-oriented route choice model is essential. There is no point in further increasing modelling complexity without a sensible level of potential gain.

The value of a calibrated route choice model, as we see it in this research, is two fold. First, a credible route choice model is capable of accurately predicting drivers route choice decisions. Route choice predictions for a population of drivers in a traffic network are directly translated into link flows. Link-flow predictions are key inputs to most transportation operational and planning activities. Hence the need for prediction accuracy is vital. Second, a wealth of information is encapsulated inside the values of estimated route choice model parameters. The sensitivity of parameter values to different situation/personal factors significantly contributes to an increased understanding of the process we are modelling. Based on an enhanced realistic understanding of the route choice decision-making process, effective operational techniques to influence drivers' route choice decisions could be achieved.

In terms of prediction accuracy, the potential gains of the developed operational process-oriented model are revealed when compared to a structural-oriented one (based on the original MAPE indicators). The structural-oriented estimation results reveal accurate choice predictions in terms of choice percentages alone. However, a severe deterioration in the model performance is depicted when the time dimension is incorporated. Estimated deliberation time frames, within the structural approach, are unrealistic and significantly different from observed ones.

Alternatively, in the process-oriented modelling approach, internally/externally imposed deliberation time frames are key determinants of final choice decisions. Situational factors (such as information form, information reliability, and choice context) and personal factors (such as gender) interact to formulate drivers' internally imposed limits on the deliberation time frames. The choice environment plays its role in allocating a feasible time frame for the undertaken deliberation process. Based on the conducted experimental/sensitivity analysis, significant impacts of the internally and externally imposed deliberation time frames in compliance behaviour are revealed. Figure 8.7 presents a simulated second-by-second preference evolution throughout an en-route deliberation process, based on a random simulated run of the calibrated DFT route choice model (ED-model, male group, sub-group 2, under DHL). The impact of time pressure on reversing choice decisions can be clearly observed.

From a process-understanding perspective, reversed impact trends of situational/personal factors on decision parameter values are revealed under the structural-oriented estimation approach, compared to the process-oriented one. Higher values of attribute weights, within the structural approach, reflect a tendency to achieve unrealistic instantaneous choice decisions. A false magnified sensitivity of decision parameters to information reliability is estimated. Reversed impact trends of situation factors on the formulation of the internally imposed deliberation frames are revealed.

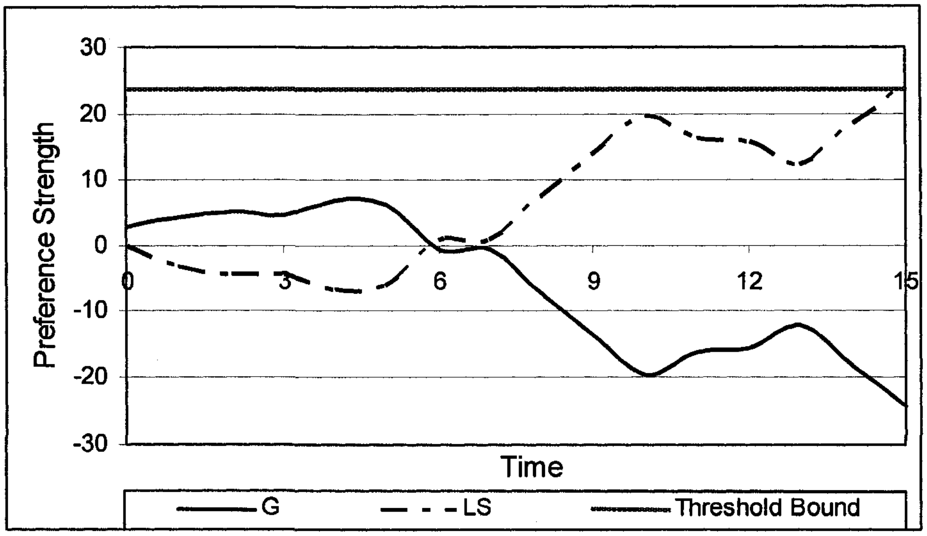


Figure 8.7 Preference Evolution Chart

In conclusion, the process-oriented modelling approach significantly contributes to increasing the credibility of the modelling process. More accurate, generalized predictions are envisioned from a full-fledged version of the developed DFT route choice model. An enhanced understanding of the underpinnings of the decision-making process is a natural outcome of a process-oriented model. Results from this research vividly indicate the potential payoff from further investigating process-oriented models.

9 CONCLUSIONS AND RECOMMENDATIONS

9.1 Précis

This chapter presents a brief summary of the overall research effort and a review of the main conclusions. The conclusions are discussed in four dimensions. First, the main findings of the experimental analysis of drivers' route choice patterns are appraised. Second, a discussion of the main conclusions of the route choice model parameter estimation results is presented. Third, the sensitivity of the deliberation process to time pressure constraints is reviewed. Finally, and in light of our findings, we step back and examine the big picture: reassessing the value of adopting a process-oriented modelling approach for drivers' route choices. Afterwards, we highlight the contributions of this research. The chapter concludes with recommendations for future research.

9.2 Summary

The objective of this research is to understand and model the deliberation process underlying drivers' route choices. This objective is motivated by the profound need to enhance the understanding of drivers' route choice behaviour, at the disaggregate individual level. This understanding is essential for many ITS applications. In formulating our behavioural perspective of the dynamic route deliberation process, our focus is on the time-dependent psychological and mental process of preference formation in an uncertain and time-pressed choice environment. This perspective is inspired by recent advances from the field of decision-making psychology.

First, a thorough literature review of the adopted modelling approaches for drivers' route choices is undertaken. The utility-maximization principle has, historically, been the conventional decision rule of most route choice modelling frameworks. Several modelling attempts have departed from the formal utility-maximization paradigm and adopted more behaviourally realistic frameworks. However, there remains a lack of a realistic representation of the dynamic deliberation process involved in route choices. Modelling of drivers' choices is mainly perceived from a structural-oriented perspective; where a relationship is formulated between a set of inputs (choice situation attributes) and outputs (choices) without a realistic understanding of the underlying psychological process. As such, the need for a process-oriented modelling perspective of drivers' route choices is realized.

We propose a theoretical framework for route choice modelling based on Decision Field Theory (DFT) from the field of psychology. DFT founded by Busemeyer and Townsend (1993) aims to understand and explain the motivational and cognitive processes underlying choice decision in uncertain choice environments. DFT provides a formal description of the dynamic evolution of preferences during deliberation. Based on the theoretical background of DFT, a route choice modelling framework is formulated for pre-trip and en-route choice decisions. Three choice situations are discussed that vary in the level of traveller information presented to the driver, namely; no information, descriptive information (congestion states) and prescriptive information (specific route guidance). For each of the three cases, a DFT route choice model is defined through: (1) a schematic representation, (2) decision variables, and (3) decision parameters.

In order to facilitate comprehensive and realistic route choice experimentation that allows for capturing the deliberation process, we developed a low cost but useful mixed-reality simulation testbed. The mixed reality simulator integrates a driving device (steering wheel) into Paramics, a microscopic traffic simulation platform. The developed system enables a driver to externally control the *lateral* and *routing* movements of a single vehicle of choice (driven vehicle) in a simulated network using a steering wheel. The designed system architecture is based on three basic components; Input Capturing (IC), Inter-Process Communication (IPC), and several Paramics API plug-ins. IC is concerned with depicting external acts on the attached driving device; translating them into movement directions. A number of Paramics API plug-ins' are coded to: (1) override Paramics default lane-changing and route choice models for the driven vehicle, (2) allow for traveller information dissemination, and (3) control the driver/simulator interface. Finally, a shared memory protocol along with an inter-process communicator is designed to allow IC application and Paramics plug-ins to communicate without delays.

An experimental procedure is designed to collect route choice data in a laboratory setting. The test network is part of the Gardiner/Lakeshore major corridor on the waterfront of downtown Toronto. Manipulation of traffic conditions is performed to maintain the real life competitiveness between the two alternative routes; Gardiner

Expressway and Lakeshore Blvd. Different information provision scenarios are adopted (different forms, and different information reliability levels).Two sets of route choice experiments are designed, using the same network but with two different tools. The first tool is a map-based one, where subjects perform their routing decisions for an imaginary trip on a computer screen with map view of the test network using mouse clicks. On the other hand, the second set is performed on the developed mixed reality platform, where subjects navigate their vehicles in a microscopic reproduction of the test network.

The developed experimental platforms and setup are used to monitor and record drivers' route choice behaviour under varying conditions. The captured behaviour is thoroughly analyzed based on ANOVA testing. The analysis of route choice behavioural patterns estimated from the conducted laboratory experiments are grouped into two levels. The first level is concerned with the assessment of decision patterns for each choice context (pre-trip and en-route) independently. Results of the map-based experiment are used for the analysis of pre-trip choice behaviour. The analysis is focused on the assessment of the impact of some key personal/situation factors on drivers' route choices, namely; information dissemination, gender, and risk attitude. En-route choice behaviour is, alternatively, observed from the mixed-reality driving experiment. The second level is concerned with the assessment of the value of the experimental procedures (map-based vs. mixed-reality) as data collecting tools. A comparative analysis is, hence, undertaken. Route choice attitudes are compared under identical situational conditions for both experimental procedures.

Given the demonstrated superiority of the mixed reality simulator in capturing the route choice decision process, recorded data are used to calibrate the DFT model. Estimation of model parameters is based on the minimization of prediction errors using Genetic Algorithms (GA) as an optimization tool. A GA parameter estimation platform is designed for the problem in hand. Predictions are based on computer simulation of route choice behaviour using the DFT model. Observed measures (choice percentages and MDTs) are aggregated based on: gender group, information reliability level sub-group, deliberation situation, and information scenario. Deliberation situations include: Pre-trip No information (PN), En-route Descriptive information (ED), and En-route Prescriptive (EP). As such, decision parameters are estimated, for each sub-group, for each deliberation model (PN-model, ED-model, and EP-model). Within each deliberation model, different information scenarios represent different decision variables (different independent variables). A multilevel step wise estimation methodology is adopted. While the multilevel approach is concerned with the within-group similarities in parameters values, for a specific deliberation model, the step wise approach focuses on the between-deliberation model similarities. Estimation results are subsequently synthesized to capture within-group, and between-groups variations in estimated parameter values.

A sensitivity analysis of route choice behaviour to the dynamics of the deliberation process is conducted, with attention focused on deliberation time. The calibrated DFT route choice model (for the male group) is used to simulate drivers' compliance attitudes under different frames of time constraints. Two information scenarios are examined; DHL and PLS. Sub-group choice percentages are estimated for each information scenario, under each considered time frame. As the adopted information scenarios are both challenging (favouring the Lakeshore), compliance rates are estimated to be the Lakeshore choice percentages.

Finally, an assessment of the added-value of the developed process-oriented route choice model is conducted by benchmarking its performance against a structural-oriented version of the model. The structural-oriented version is realized by re-estimating the DFT model parameters based on choice percentages, with no time dimension. Ignoring the dynamics of the decision process during the estimation process reduces the DFT model to a structural one.

9.3 CONCLUSIONS

The following sections discuss the main findings of this research.

9.3.1 Experimental Analysis

Experimental data from the map-based and mixed reality experiments are analyzed independently as well as comparatively. Conclusions from the statistical analysis are summarized with respect to: (1) route choice behavioural patterns, and (2) potential of experimentation tools.

1. Route Choice Behavioural Patterns

Results of the map-based experiment are used for the analysis of pre-trip choice behaviour. The following are the main findings:

- Under no information provision, an intuitive preference to use the expressway is revealed (in about 88% of the trips). However, a change in drivers' preferences is depicted in an occasional basis (in the remaining 12%). This finding strengthens the notion of a stochastic decision-making process.
- Information content has a significant impact on drivers' route choices. Drivers' pre-trip choices are significantly altered when receiving traffic information that substantially challenges their expectations. This finding coincides with earlier route choice literature pertaining to assumptions of bounded-rationality, and conflict assessment and resolution theories.
- A significant impact of the variation of information reliability (from 0.6 to 0.8 reliability levels) is observed on drivers' pre-trip route choices. This implies that pre-trip choices are sensitive to slight variations in information accuracy.
- Gender differences play a significant role in drivers' responses to disseminated traffic information. This impact is more pronounced under the reduced information reliability level. As the reliability level increases, gender impact diminishes.

Mixed reality experimental results are used for the analysis of en-route diversion decisions. The following are the main findings:

- Information content has a significant impact on drivers' en-route diversion decisions. Bounded-rationality behaviour is, however, revealed in divergence decisions. Drivers partially resist divergence when perceived travel time gains are not considerable. The interaction between compliance and inertia control drivers' diversion attitudes.
- The impacts of gender differences, and information reliability, are less perceived in en-route diversion decisions. The significant impacts of compliance and inertia on drivers' divergence decisions dominate all other investigated factors.

2. Benefits of the Mixed Reality Experimentation Tool

Results of the conducted statistical analysis highlight the significant impact of the adopted testing procedure in route choice experimental observations. The following can be concluded:

- Map-based testing procedure is capable of portraying a generic picture of route choice behaviour and is thus well-suited for qualitative high-level assessments. No severe unexplained deviations of the map-based procedure results are encountered in relevance to previous findings in route choice literature.
- The mixed reality experimental platform has a potential to enhance the realism of in-lab simulated route choice experiments and hence improves the credibility of collected data. The virtual reproduction of the choice environment, and the tangible consequences of choice decisions contribute to a more serious testing environment. Nonetheless, obtaining large sample sizes within the mixed reality environment is a challenge.

9.3.2 Operational DFT Route Choice Model

Estimation of DFT route choice model parameters is performed based on a multi-level step-wise estimation methodology. Aggregate observed measures for a number of data groups are used. A GA-based parameter estimation platform is used as an optimization tool. The main conclusions are:

- The potential of the adopted DFT modelling framework in replicating subjects' route choice attitudes is revealed through the estimated low prediction errors. Parameter estimation results report Mean Absolute Percent Error (MAPE) ranging from 0.03% to around 10%, for the estimation data.
- From a qualitative perspective, testing results are considered adequate; with MAPE ranging from around 7% to 25%. The small sample size of the test data set indicates a need for larger samples.
- Travel time attribute is considered the most salient attribute for all data groups. The role of travel distance and freeway usage attributes, in the route choice decision-making process, is less influential.

- Drivers' initial preference biases are revealed to be based on their experience-based perceptions of the choice situation attributes. Neither information type nor its reliability level impact the value of estimated initial preference biases.
- The impacts of information reliability levels within ED-models are manifested in the values of two parameters: information weight and threshold bound. As information reliability increases, the values of both parameters increase. The increase in estimated threshold bounds reflect a more serious deliberation process; an attempt to make more mature decisions.
- The impacts of information reliability levels within EP-models are observed in the values of the compliance weight and the threshold bound parameters. No impact is estimated on the attribute attention probabilities, including the compliance attribute. The increase in information reliability level results in an increase in the values of both affected parameters.
- A variation in the value of estimated threshold bounds is revealed under different choice situations (ED, EP, and PN-models). The highest value is estimated for ED-models. The explicit advice to take a certain route (in EP-models) results in a decrease in estimated threshold bounds. Threshold bound values decreased considerably in pre-trip choices with no information provision. The absence of traffic information together with the urge to start the trip encourages drivers to adopt partially habitual choice attitudes.
- The following gender differences are observed in estimated model parameters:
    a. Higher attribute weights are revealed for the female group for the travel time and compliance attributes. An increased consideration of travel time gains and information recommendations are, hence, revealed for the female group. Alternatively, a lower value of the freeway usage attribute weight is estimated for the female group. This reflects a reduced significance of the payoff of the freeway usage attribute on females' decision-making process.
    b. An increased level of bias in initial preferences is estimated for the male group for both pre-trip and en-route deliberation models. However, an increased sensitivity of the level of bias to the choice context (pre-trip vs en-route) is revealed for the female group.

c. An increased sensitivity of the information weight parameter of ED-models to information reliability is observed for the male group. Males tend to lose confidence in disseminated descriptive-type information more vigorously.

d. An increased sensitivity of the compliance attention probabilities and the threshold bounds, of EP-models, to information reliability is observed for the female group. In the presence of specific advice, the impact of information reliability is more pronounced in the females' route choice attitudes.

9.3.3 Dynamics of Route Deliberation

Time pressure constraint is a common situational factor that has a significant impact on drivers' route choice attitudes. As such, a sensitivity analysis on drivers' compliance behaviour to variations in deliberation time frames is undertaken. The developed DFT route choice model is used to generate simulated route choice data. En-route simulated route choice data, under information scenarios that opposed drivers' inclinations, is adopted. The following are the main findings:

- A significant impact of time pressure constraints on compliance behaviour is estimated for both descriptive and prescriptive information scenarios.
- Completely different behavioural trends are revealed under different information scenarios. Under the descriptive information scenario, increased compliance rates are estimated with the relaxation of the time pressure constraint. This trend is observed under higher perceived information reliability level. As the information reliability level decreases, compliance rates are lower, and less sensitive to time pressure constraints. The practical implication of this finding is that if travellers are not provided with sufficiently accurate information and sufficiently long time to deliberate it, they are less likely to comply.
- A reversed behavioural trend is revealed under prescriptive information. Under tight time pressure constraint, drivers are more inclined to comply with explicit advice, as there is no time for further deliberation. As such, a decrease in compliance rates is estimated with increased deliberation time frames. Information impacts are more pronounced under increased reliability levels.

9.3.4 Process-oriented vs Structural-oriented Route Choice Modelling

The dynamic nature of the route choice deliberation process is one of the main aspects motivating the adoption of a process-oriented modelling framework. For comparative analysis, a structural-oriented parameter estimation methodology is adopted to re-estimate the conceptual model parameters of the male group. The main conclusions are:

- Re-estimation results reveal considerable differences in estimated parameter values as well as performance indicators. The performance of the structural model, based on the modified MAPE without MDT, is misleadingly superior to the process oriented one. Substantially low values of the Modified-MAPEs are estimated ranging from 0 to 0.02%. Reasonably low testing error values are also estimated for the Modified-MAPE, ranging from 7 to 12%. However, when the structural model is evaluated based on errors in predicting both choice percentages and deliberation times, the performance substantially deteriorates (MAPE ranging from 23 to 33% for estimation data, and 25% to 35% for test data), well below the performance of the process model.
- Major inconsistencies between predicted and observed deliberation time frames are estimated using the structural model. This reveals a reduced credibility in predicting the deliberation process. As such, the generalization of this type of model could result in mis-predictions.
- From a process-understanding perspective, significantly different (often reversed) impact patterns of situational/personal factors are estimated under the structural estimation methodology, compared to the process one. The main differences are highlighted in the following:
  a. Higher values of attribute weights are estimated for the structural-oriented model. The increase in attribute weights reflects a tendency to achieve unrealistic instantaneous choice decisions.
  b. A magnified sensitivity of information reliability in varying information weights is estimated for the structural-oriented ED-model.
  c. A substantially different trend for impact of information characteristics (form, and reliability) on the value of estimated threshold bounds is observed.

9.4 CONTRIBUTIONS

The following is a brief summary of the main contributions of this research:

1. Developing a process-oriented conceptual framework for drivers' route deliberation processes (pre-trip and en-route). The developed conceptual framework is founded on the basis of DFT theoretical abstraction of the decision-making process. DFT, developed by Busemeyer and Townsend (1993), is one of a few process-oriented behavioural decision theories that explicitly accounts for varying degrees of uncertainty as well as time pressure in an integrated scientifically sound framework. The developed framework is targeted to model how decisions are made and how preferences evolve with time. To the best of the author's knowledge, the developed route choice model is the first modelling attempt that explicitly addresses the dynamics of the decision-making process by incorporating the deliberation time dimension into its framework.
2. Developing an integrated framework for information provision within a process-oriented route choice modelling framework. The developed conceptual framework accounts for descriptive and prescriptive information provision. The product is a set of process-oriented deliberation models that abstract drivers' decision-making processes in three information related scenarios: no information, descriptive information, and prescriptive information scenarios.
3. Developing an operational version of DFT route choice model. Decision parameters are estimated for the adopted conceptual framework for PN, ED, and EP-models. Estimation of the model parameters is based on experimental observations from a limited, homogenous, sample size of drivers. An elaborate estimation procedure using modern evolutionary optimization techniques was developed for model calibration.
4. Enhancing the understanding of the impact of time pressure constraints on drivers' compliance attitudes, under descriptive and prescriptive information provision. Based on the developed operational DFT route choice model, simulated route choice observations are adopted to analyze the sensitivity of drivers' compliance attitude to varying levels of time pressure. Variations in impact trends are estimated with varying information characteristics (form, and reliability). To

the best of the author's knowledge, this research is the first attempt to analyse the effect of time pressure in drivers' compliance behaviour.

5. Developing a simple mixed reality infrastructure for experimental analysis of route choice behaviour under various ITS applications. The developed platform allows a test driver to navigate a vehicle through a microscopic reproduction of a full scale traffic network. This is achieved through the integration of a PC-steering device into Paramics microscopic traffic simulator. Experimental controls (traffic patterns, information provision...etc.) are user-defined. Detailed observations, such as network conditions (travel times, congestion states...etc.), and drivers' responses (choices and deliberation times) are seamlessly recorded. This platform offers a credible cost-effective data collection ground for drivers' route choice behaviour. The developed platform is realized to enhance the realism of in-lab simulated route choice experiments and hence improve the credibility if collected data.
6. Enhancing the understanding of the influences of traffic information characteristics on drivers' route choice behaviour. Using the experimental observations, the statistical significance of the impacts of information characteristics (form, content, and reliability) on drivers' route choice attitudes are evaluated.
7. Enhancing the understanding of the differences between structural-oriented and process-oriented models. The value of process-oriented models is clearly established.

9.5 RECOMMENDATIONS

This research identifies a potentially very useful direction for future research in route choice modelling. Despite the achievements in this research, ample room exists for future enhancements and expansions. The following are a few thoughts on the envisioned future extensions of our work:

1. Understanding and modelling of the variation trend of drivers' initial preference biases under different situational conditions (different perceived traffic patterns). Drivers' deliberation processes start from certain levels of initial biases. The

effects of these levels on the deliberation processes outcomes are, in many cases, significant. Drivers' initial preference biases are revealed to be experience-dependent with no information influences. As such, estimated levels are expected to be influenced by perceived attributes of the choice situation. This influence mechanism needs to be properly understood and modelled.

2. Further understanding and modelling of the variation trend of drivers' threshold bounds with situational conditions. Different levels of threshold bounds are estimated for each driver, under various choice scenarios (choice context, and information characteristics). Threshold bounds are the termination parameters of the internally controlled deliberation processes. Thus, understanding and modelling of the influences of situational conditions in the formulation of drivers' threshold bounds is of prominent importance in the development of a generic DFT route choice model.
3. Further understanding and modelling of the impact of different information reliability levels on relevant DFT route choice model parameters. A significant variation of estimated values of some parameters is revealed for the considered two information reliability levels (0.6 and 0.8). Other reliability levels are to be tested in an attempt to identify an impact trend.
4. The assessment of the impact of time pressure constraints on drivers' route choice attitudes based on experimental observations. The intended analysis is envisioned to be based on a set of simulated driving experiments where subjects are to receive traffic information at different time spots prior to diversion.
5. The assessment of the impact of different information communication technologies on drivers' route choice behaviour (auditory vs. visual display, on-board navigation system vs. VMS).
6. The assessment of the credibility of laboratory collected route choice data based on a comparative analysis between experimentally observed vs. real-life route choice behavioural patterns. Diversion rates from field data could be used to perform this type of analysis.
7. Analysis of drivers' route choice behaviour under different choice scenarios with respect to the payoffs of the decision attributes. A representation of various

combinations of the payoffs of the choice attributes is essential in the calibration of a generic full-fledged DFT route choice model. The experimental analysis undertaken in this research is based on route choice observations for the adopted test network. The test network is composed of two alternative routes. The variation in the payoff of the distance attribute, between the two routes, is limited to 22%. Testing a wide spectrum of variations of payoffs is necessary for obtaining generic results.

8. Developing a generic operational DFT route choice model, where a probability distribution is defined for each of the model parameters, for each identified homogenous group of drivers (with the considerations of recommendations 1, 2, 3, 4, and 5). Parameters distributions need to be related to different personal/situation factors (such socio-economic characteristics, information characteristics, choice context ...etc). The operation of the generalized DFT route choice model is envisioned through sampling the model parameters from estimated parameters distributions, given drivers' characteristics and situational conditions. Estimation of parameters distributions should be based on wide-scope experimentation. A large cross-sectional type sample of drivers is envisioned for this purpose. Drivers' route choices are to be monitored for a number of different experimental controls (different OD pairs with different experimental setups).
9. Benchmarking the performance of the developed DFT route choice model against a classical logit route choice model. The incorporation of the deliberation time dimension within a logit model could be attained by specifying narrow ranges of deliberation time frames (deliberation time bins) and dividing the route choice data accordingly. A different logit model is to be calibrated for each deliberation time range. The differences or indifferences between calibrated models would shed light into the significance of the impact of the deliberation time dimension on drivers' decision-making process. The added-value of the developed process-oriented model could, hence, be assessed.
10. Extending the developed mixed reality platform to include longitudinal control (such as speed and acceleration) of the driven vehicle. A game-type pedal is to be used as an input device to capture longitudinal control actions by the driver of the

subject vehicle. These actions will override the internal car-following model in Paramics, only for the driven vehicle. This extension is intended to enable wider research utility of the developed system.

11. Integrating the developed route deliberation model with a process-oriented model of drivers' learning process (day-to-day and day-specific learning). The decision making aspects and the learning aspects of route choice are highly intertwined both in reality and in the modelling literature. One can think of route choice as perhaps one coin with two sides; a learning process side and a decision making side. A comprehensive process-oriented route choice model should be based on seamlessly integrated decision/learning models. As such, a process-oriented learning model should focus on updating the values of the DFT decision variables (Anticipated states probabilities, *ASPs*; and payoffs, *M*) based on previous/current experiences. The interaction between the DFT model and the learning one needs to be cyclic; where outputs of each model are inputs to the other.
12. Integrating the developed route deliberation model with process-oriented models of driver choice-set formulation, and information-acquisition processes. A comprehensive process-oriented route choice model is envisioned as a final product.

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APPENDIX A: PRE-EXPERIMENTATION QUESTIONNAIRE

ID Code	

Socioeconomic/Demographic Characteristics

1. Age
   i) 18-29
   ii) 30-39
   iii) 40-49
   iv) 50-59
   v) 60+

2. Gender
   i) Male
   ii) Female

3. Occupation/Education
   i) Graduate Student
   ii) Undergraduate Student

4. Income
   i) Up to $20,000
   ii) $20,000 - $40,000
   iii) $40,000 - $60,000
   iv) $60,000 - $80,000
   v) $80,000 - $100,000
   vi) $100,000+

ID Code	

Personality factor: Adventure and Discovery Attitude

1. I like discovering new routes to get someplace
   i) Strongly Disagree
   ii) Disagree
   iii) Neutral
   iv) Agree
   v) Strongly Agree

2. I sometimes do things just to see if I can
   i) Strongly Disagree
   ii) Disagree
   iii) Neutral
   iv) Agree
   v) Strongly Agree

3. I am willing to take risks to avoid traffic delays
   i) Strongly Disagree
   ii) Disagree
   iii) Neutral
   iv) Agree
   v) Strongly Agree

4. I like exploring new places
   i) Strongly Disagree
   ii) Disagree
   iii) Neutral
   iv) Agree
   v) Strongly Agree

5. I am not afraid of getting lost in Toronto
   i) Strongly Disagree
   ii) Disagree
   iii) Neutral
   iv) Agree
   v) Strongly Agree

6. I would rather take a little longer to use a route I know well
   i) Strongly Agree
   ii) Agree
   iii) Neutral
   iv) Disagree
   v) Strongly Disagree

ID Code	

Route Choice Attitude

When I choose my route

1. I focus on travel times of alternative routes
   i) Only
   ii) Mostly
   iii) Occasionally
   iv) Not at all

2. I focus on travel distances of alternative routes
   i) Only
   ii) Mostly
   iii) Occasionally
   iv) Not at all

3. I focus on whether its a freeway or a surface street
   i) Only
   ii) Mostly
   iii) Occasionally
   iv) Not at all

4. I prefer taking a freeway than a surface street
   i) Disagree
   ii) Neutral
   iii) Agree

ID Code	

Driving Experiences

1. How long have you been driving?
   i) Not at all
   ii) Less than 2 years
   iii) From 2 to 5 years
   iv) From 5 to 10 years
   v) More than 10 years

2. While driving, are you familiar with receiving traffic information from variable message signs?
   i) No
   ii) Yes

3. Did you drive before on the Gardiner Corridor?
   i) No
   ii) Yes

   If yes: How often?

   i) Just once or twice
   ii) From time to time
   iii) A lot

4. Did you drive before on the Lakeshore Blvd?
   i) No
   ii) Yes

   If yes: How often?

   i) Just once or twice
   ii) From time to time
   iii) A lot

APPENDIX B: ANALYSIS OF VARIANCE (ANOVA)

B.1 ANOVA BASICS

B.1.1 Introduction

ANOVA is a classical versatile technique for obtaining causal inferences from the measurements of a controlled experiment (Weiss, 2006). ANOVA is applied on experimental measures to assess the effect of a set of defined factors on a response variable of interest. ANOVA is built on the ground of testing the hypothesis of the equality of means of two or more populations. The underlying method is based on partitioning the total variance of the variable of interest into its components (systematic and random components). The effect of the significantly contributing factors would appear on the systematic component, while insignificant contributions are within the random component.

In our research, ANOVA is consulted to assess the significance of a set of personal/situational factors on route choice behaviour. Two experimental measures are adopted as response variables; Gardiner choice percentages (%G), and Mean Deliberation Time (MDT). Two analysis layouts are consulted; one-way ANOVA, and two-way ANOVA with replications. In the following sections, basic overviews of both layouts are presented.

B.1.2 One-way ANOVA

One way ANOVA is concerned with testing the effect of some factor A in a response variable y. Lets assume that an experiment is performed where different measurements of the response variable y is measured repeatedly (i times) under m different levels of factor A (A_1 to A_m). As such, y_{ij} is the i^{th} observation under treatment A_j. Resulting measurements from such an experiment could be tabulated as shown in Table B.1.

Table B. 1 One Way ANOVA Experimental Layout

A_1	A_2	A_3	....	A_m
y_{11}	y_{21}	y_{31}		y_{m1}
y_{21}				
$y_{n,1}$				$y_{n,m}$

The response variable could be represented by:

$y_{ij} = \mu + \delta j + \varepsilon ij$

Where,

μ: is the population mean

δ: is factor effect

ε: represent random variations $N(0, \sigma^2)$

To assess whether factor A is significant or not, we shall test the following hypothesis;

H_0: $\delta_1 = \delta_2 = ...\delta_m = 0$

H_1: $\delta_1, \delta_2, ...\delta_m$ aren't all zeros

Testing the above hypothesis is summarized in Table B.2. Given That;

$$S_D = \sum\sum y_{ij}^2 - n\bar{y}^2$$
$$S_A = \sum\sum(\bar{y}_j - \bar{y})^2$$
$$S_E = S_D - S_A$$

Table B. 2 One-way ANOVA Analysis

Source Of Variation	**Sum of Square**	**Degrees of Freedom**	**Mean Square**	**F-ratio Test**
Between samples	S_A	m-1	$\frac{S_A}{m-1}$	$\frac{S_A/(m-1)}{S_E(n-m)}$
Within Samples	S_E	n-m	$\frac{S_E}{n-m}$	
Total	S_D	n-1		

Accordingly, H_0 is rejected under (100- α) % confidence interval if:

$$\frac{S_A/(m-1)}{S_E(n-m)} > F_{m-1,\, n-m;\alpha}$$

In other words, H_0 is rejected if the probability (P-value) corresponding to the calculated F-value, under the respectable degrees of freedom, is larger than the specified significance level (α). If H_0 is rejected, this means that there is, indeed, a significant effect of factor A in the response variable y, under the specified confidence interval.

B.1.3 Replicated Two-way ANOVA

Two way ANOVA tests, in general, are concerned with testing the effects of two factors A and B on a response variable y. Results from theses tests report the significance of the independent effect of each of the tested factors on the response variable. In many research cases, investigating the interaction between factors could be of interest. The interaction between factors is simply the significance of specific combinations of different levels of both factors. The addition of this analysis dimension mandate increasing the amount of collected data. Replicated two-way ANOVA tests are, therefore, consulted. Table B.3 presents a general layout of a replicated two-way ANOVA experiment, where for each combination of the i^{th} level of factor A and the j^{th} level of factor B, there exist t observations y_{ijk} (k= 1 to t).

The response variable could be represented by:

$$y_{ij} = \mu + \delta_{i\bullet} + \delta_{\bullet j} + \lambda_{ij} + \varepsilon ij$$

Where,

μ: is the population mean

δ: is factor effect

ε: represent random variations $N(0, \sigma^2)$

Table B. 3 Two-Way ANOVA Experimental Layout

	$\mathbf{B_1}$	$\mathbf{B_2}$	$\mathbf{B_j}$	**....**	$\mathbf{B_m}$
A_1	y_{111} ... y_{11t}	y_{121} y_{12t}	y_{1j1} y_{1jt}	····	y_{1m1} y_{1mt}
....	....	....	....	....	....
A_i	y_{111} y_{i1t}	y_{i21} y_{i2t}	y_{ij1} y_{ijt}	....	y_{im1} y_{imt}
....	....	....	....	....	....
A_n	y_{n11} y_{n1t}	y_{n21} y_{n2t}	y_{nj1} y_{njt}	....	y_{nm1} y_{nmt}

Three hypotheses could, then, be evaluated.

First: To assess whether factor A is significant or not, we shall test the following hypothesis;

H_0: $\delta_{1\bullet} = \delta_{2\bullet} = ...\delta_{n\bullet} = 0$

H_1: $\delta_{1\bullet}, \delta_{2\bullet}, ...\delta_{n\bullet}$ aren't all zeros

Second: To assess whether factor B is significant or not, we shall test the following hypothesis;

H_0: $\delta_{\bullet 1} = \delta_{\bullet 2} = ...\delta_{\bullet m} = 0$

H_1: $\delta_{\bullet 1}, \delta_{\bullet 2}, ...\delta_{\bullet m}$ aren't all zeros

Third: To assess whether the interaction between factors A and B is significant or not, we shall test the following hypothesis;

H_0: $\lambda_{11} = \lambda_{12} = ...\lambda_{nm} = 0$

H_1: $\lambda_{11}, \lambda_{12}, ...\lambda_{nm}$ aren't all zeros.

Testing the above hypotheses are summarized in Table B.4. Given That;

$$T_{ij\bullet} = \sum_{k=1}^{t} y_{ijk}$$

$$T_{i\bullet\bullet} = \sum_{j=1}^{m}\sum_{k=1}^{t} y_{ijk}$$

$$T_{\bullet j\bullet} = \sum_{i=1}^{n}\sum_{k=1}^{t} y_{ijk}$$

$$G = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{t} y_{ijk}$$

$$SS = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{t} y_{ijk}^{2}$$

$$S_A = \sum_{i=1}^{n} \frac{T_{i\bullet\bullet}^{2}}{mt} - \frac{G}{nmt}$$

$$S_B = \sum_{j=1}^{m} \frac{T_{\bullet j\bullet}^{2}}{nt} - \frac{G}{nmt}$$

$$S_I = \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{T_{ij\bullet}^{2}}{t} - \frac{G}{nmt} - S_A - S_B$$

$$S_E = SS - \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{T_{ij\bullet}^{2}}{t}$$

$$S(Y^2) = SS - \frac{G^2}{nmt}$$

Table B. 4 One-way ANOVA Analysis

Source Of Variation	**Sum of Square**	**Degrees of Freedom**	**Mean Square**	**F-ratio Test**
Factor A	S_A	n-1	$\frac{S_A}{n-1}$	$\frac{nm(t-1)S_A}{(n-1)S_E}$
Factor B	S_B	m-1	$\frac{S_B}{m-1}$	$\frac{nm(t-1)S_B}{(m-1)S_E}$
Interaction	S_I	(n-1)(m-1)	$\frac{S_I}{(n-1)(m-1)}$	$\frac{nm(t-1)S_I}{(n-1)(m-1)S_E}$
Error	S_E	nm(t-1)	$\frac{S_E}{nm(t-1)}$	
Total	$S(Y^2)$	nmt-1		

H_0, of each of the three stated hypotheses, is rejected if the probability (P-value) corresponding to the calculated F-value, under the respectable degrees of freedom, is larger than the specified significance level (α).

B.2 ANOVA RESULTS

Table B. 5 Map-based Pre-trip Experiment, Information Significance

Test Type	Measure	Test Factors		P-value		
		Factor 1	Factor 2	Factor 1	Factor 2	Interaction
2 - Factor ANOVA	%G	All 12 scenarios	Group 1 vs Group 2	0.0009	0.0000	0.0060
1- Factor ANOVA	%G	No-info & PG	Group 1	0.3465	---	---
1- Factor ANOVA	%G	No-info & PLS	Group 1	< 0.0001	---	---
1- Factor ANOVA	%G	No-info & DHH	Group 1	0.7288	---	---
1- Factor ANOVA	%G	No-info & DHM	Group 1	< 0.0001	---	---
1- Factor ANOVA	%G	No-info & DHL	Group 1	< 0.0001	---	---
1- Factor ANOVA	%G	No-info & DMH	Group 1	0.8957	---	---
1- Factor ANOVA	%G	No-info & DMM	Group 1	0.7021	---	---
1- Factor ANOVA	%G	No-info & DML	Group 1	< 0.0001	---	---
1- Factor ANOVA	%G	No-info & DLH	Group 1	0.2465	---	---
1- Factor ANOVA	%G	No-info & DLM	Group 1	0.2823	---	---
1- Factor ANOVA	%G	No-info &DLL	Group 1	0.9989	---	---
1- Factor ANOVA	%G	No-info & PG	Group 2	0.5111	---	---
1- Factor ANOVA	%G	No-info & PLS	Group 2	0.0019	---	---
1- Factor ANOVA	%G	No-info & DHH	Group 2	0.9083	---	---
1- Factor ANOVA	%G	No-info & DHM	Group 2	0.0013	---	---
1- Factor ANOVA	%G	No-info & DHL	Group 2	0.0000	---	---
1- Factor ANOVA	%G	No-info & DMH	Group 2	0.9888	---	---
1- Factor ANOVA	%G	No-info & DMM	Group 2	0.8243	---	---
1- Factor ANOVA	%G	No-info & DML	Group 2	0.0002	---	---
1- Factor ANOVA	%G	No-info & DLH	Group 2	0.2376	---	---
1- Factor ANOVA	%G	No-info & DLM	Group 2	0.5709	---	---
1- Factor ANOVA	%G	No-info &DLL	Group 2	0.5834	---	---
2 - Factor ANOVA	MDT	All 12 scenarios	Group 1 vs Group 2	0.0045	0.1269	0.9999
1- Factor ANOVA	MDT	No-info & PG	All subjects	0.5525	---	---
1- Factor ANOVA	MDT	No-info & PLS	All subjects	0.1085	---	---

1- Factor ANOVA	MDT	No-info & DHH	All subjects	0.0004	---	---
1- Factor ANOVA	MDT	No-info & DHM	All subjects	0.0012	---	---
1- Factor ANOVA	MDT	No-info & DHL	All subject	0.0111	---	---
1- Factor ANOVA	MDT	No-info & DMH	All subjects	0.0042	---	---
1- Factor ANOVA	MDT	No-info & DMM	All subjects	0.0051	---	---
1- Factor ANOVA	MDT	No-info & DML	All subjects	0.0041	---	---
1- Factor ANOVA	MDT	No-info & DLH	All subjects	0.1287	---	---
1- Factor ANOVA	MDT	No-info & DLM	All subjects	0.3449	---	---
1- Factor ANOVA	MDT	No-info &DLL	All subjects	0.3343	---	---

Table B. 6 Map-based Pre-trip Experiment, Gender Significance

Type	Measure	Test Factors		Significance		
		Factor 1	Factor 2	Factor 1	Factor 2	Interaction
ANOVA	%G	All 12 scenarios	Group 1- M vs F	0.055	0.268	0.05
ANOVA	%G	Gender - PG	Group 1	< 0.0001	---	---
ANOVA	%G	Gender - PLS	Group 1	0.921	---	---
ANOVA	%G	Gender - DHH	Group 1	0.193	---	---
ANOVA	%G	Gender - DHM	Group 1	0.498	---	---
ANOVA	%G	Gender - DHL	Group 1	0.94	---	---
ANOVA	%G	Gender - DMH	Group 1	0.528	---	---
ANOVA	%G	Gender - DMM	Group 1	0.023	---	---
ANOVA	%G	Gender - DML	Group 1	0.549	---	---
ANOVA	%G	Gender - DLH	Group 1	0.013	---	---
ANOVA	%G	Gender - DLM	Group 1	0.001	---	---
ANOVA	%G	Gender - DLL	Group 1	0.113	---	---
ANOVA	%G	All 12 scenarios	Group 2- M vs F	0.004	0.375	0.313
ANOVA	MDT	All 12 scenarios	All- M vs F	0.001	0.257	0.427

Table B. 7 Map-based Pre-trip Experiment, Risk Index Significance

e	Measure	Test Factors		Significance		
		Factor 1	Factor 2	Factor 1	Factor 2	Interaction
ANOVA	%G	All 12 scenarios	Group 1- Class 1 vs Class 2	0.004	0.94	0.27
ANOVA	%G	All 12 scenarios	Group 2- Class 1 vs Class 2	0.01	0.28	0.65
ANOVA	MDT	All 12 scenarios	All subjects- Class 1 vs Class 2	< 0.0001	0.14	0.67

Table B. 8 En-route Mixed Reality Experiment, Information Significance

Type	Measure	Test Factors		Significance		
		Factor 1	Factor 2	Factor 1	Factor 2	Interaction
ANOVA	%G	All 6 scenarios	Group 1vs Group 2	< 0.0001	0.31	0.48
ANOVA	MDT	All 6 scenarios	Group 1vs Group 2	0.728	0.001	0.473

Table B. 9 En-route Mixed Reality Experiment, Resistance to Divergence Significance

Type	Measure	Test Factors		Significance		
		Factor 1	Factor 2	Factor 1	Factor 2	Interaction
ANOVA	%G	G vs LS - PG	All Subjects	< 0.0001	---	---
ANOVA	%G	G vs LS- PLS	All Subjects	0.02	---	---
ANOVA	%G	G vs LS- DHH	All Subjects	< 0.0001	---	---
ANOVA	%G	G vs LS- DHL	All Subjects	0.727	---	---

Table B. 10 En-route Mixed Reality Experiment, Gender Significance

Type	Measure	Test Factors		Significance		
		Factor 1	Factor 2	Factor 1	Factor 2	Interaction
ANOVA	%G	All 6 scenarios	All subjects- M vs F	< 0.0001	0.611	0.429
ANOVA	MDT	All 6 scenarios	Group 1- M vs F	0.859	0.001	0.473
ANOVA	MDT	All 6 scenarios	Group 2- M vs F	0.876	0.359	0.742

APPENDIX C: PARAMETER ESTIMATION RESULTS

Table C.1 Process-oriented estimation approach, Male Group, Predicted vs Observed Choice measures

Information Scenario		w_i[a]	%G			MDT		
			Observed - Estimation Data	Predicted	Observed - Test Data	Observed - Estimation Data	Predicted	Observed - Test Data
ED-model								
DHH	Sub-group 1	0.26	95	93	89	4.5	4.5	5.8
	Sub-group 2	0.14	97	100	80	9.1	9.1	7.7
DHL	Sub-group 1	0.13	58	69	50	5.2	5.1	6.2
	Sub-group 2	0.17	29	29	20	16.1	16.2	10.6
DLH	Sub-group 1	0.12	100	95	100	5	3.2	4.35
	Sub-group 2	0.05	91	100	100	9.5	4.6	10.1
DLL	Sub-group 1	0.08	100	91	100	5.8	5.8	6.6
	Sub-group 2	0.05	92	100	100	10.8	14.6	5
EP-model								
PG	Sub-group 1	0.4	97	89	96	7	7	8.1
	Sub-group 2	0.32	95	97	94	8	10.8	14.6
PLS	Sub-group 1	0.14	53	75	44	5.9	6.7	5.1
	Sub-group 2	0.14	43	71	56	9.1	9.2	8.7
PN-model								
	No info		90	90	8	3.3	3.3	3.2

a Objective function factor

Table C.2 Process-oriented estimation approach, Female Group, Predicted vs Observed Choice measures

Information Scenario		w_i^a	%G			MDT		
			Observed - Estimation Data	Predicted	Observed - Test Data	Observed - Estimation Data	Predicted	Observed - Test Data
ED-model								
DHH	Sub-group 1	0.17	86	90	---	3.3	3.6	---
	Sub-group 2	0.2	100	100	100	10.4	9.2	12.3
DHL	Sub-group 1	0.12	30	44	---	3.8	3.5	---
	Sub-group 2	0.2	15	14	17	11.9	9.2	11.8
DLH	Sub-group 1	0.05	100	97	---	3.3	2.1	---
	Sub-group 2	0.11	100	96	100	4.3	4.3	5.7
DLL	Sub-group 1	0.05	100	79	---	4.3	4.2	---
	Sub-group 2	0.1	100	100	100	4.7	12.9	5.2
EP-model								
PG	Sub-group 1	0.34	83	85	---	3.5	3.2	---
	Sub-group 2	0.42	100	100	100	6.2	6.1	8
PLS	Sub-group 1	0.08	40	39	---	1.8	2.8	---
	Sub-group 2	0.16	12	20	17	6.6	6.9	6.4
PN-model								
No info			63	66	69	3.2	3.3	4.2

a Objective function factor

Table C.3 Structural-oriented estimation approach, Male Group, Predicted vs Observed Choice measures

Information Scenario		w_i^a	%G			MDT [b]		
			Observed - Estimation Data	Predicted	Observed - Test Data	Observed - Estimation Data	Predicted	Observed - Test Data
ED-model								
DHH	Sub-group 1	0.26	95	94	89	4.5	4.3	5.8
	Sub-group 2	0.14	97	94	80	9.1	1.1	7.7
DHL	Sub-group 1	0.13	58	56	50	5.2	6.8	6.2
	Sub-group 2	0.17	29	28	20	16.1	1.1	10.6
DLH	Sub-group 1	0.12	100	100	100	5	3.6	4.35
	Sub-group 2	0.05	91	96	100	9.5	1.2	10.1
DLL	Sub-group 1	0.08	100	100	100	5.8	6.4	6.6
	Sub-group 2	0.05	92	93	100	10.8	2.3	5
EP-model								
PG	Sub-group 1	0.4	97	96	96	7	2.7	8.1
	Sub-group 2	0.32	95	95	94	8	2.6	14.6
PLS	Sub-group 1	0.14	53	54	44	5.9	3.2	5.1
	Sub-group 2	0.14	43	42	56	9.1	3.3	8.7
PN-model								
	No info		90	90	8	3.3	1.5	3.2

a Objective function factor

b Not considered during estimation