Southwest Region University Transportation Center

Dynamics of Urban Commuter Behavior Under Real-Time Traffic Information

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16. Abstract

The effectiveness of Intelligent Transportation Systems (ITS) technologies in enhancing the quality of life in congested urban and suburban areas critically depends on drivers' response to these systems and to the information capabilities that they offer. In particular, Advanced Traveler Information Systems (ATIS) aim to improve network flow conditions through the provision of real-time information to drivers, at the trip origin as well as en route. As decisions about the configuration and deployment of such potentially expensive technologies come under consideration, it is essential to develop the body of fundamental knowledge on driver decision-making processes under real-time information supply strategies. This report is structured as a behavioral research effort to examine the processes underlying commuter decisions on en-route diversions and day-to-day departure time and route choices as influenced by the provision of real-time traffic information.

This report presents a series of large-scale laboratory-like experiments in which real commuters interact with and among multiple participants in a traffic network in real-time under various information strategies through a dynamic travel simulator. This simulator considers both the supply side system performance as influenced by driver response to real-time traffic information as well as the demand-side driver behavior as influenced by real-time traffic information based on system performance. Its "engine" is a traffic flow simulator and ATIS information generator. By actually simulating traffic conditions in response to the supplied commuter decisions, the simulator provides stimuli to the participants that are always consistent with physically realistic traffic behavior, and with their previous actions.

The data collected from these experiments form the observational basis for the development and calibration of Poisson event count models of user compliance and satisfaction behavior as well as multinomial probit models of dynamic departure time and route switching decisions. By estimating these models, substantive conclusions regarding the factors influencing the commuter behavior in response to various ATIS systems are obtained, addressing key fundamental issues critical to the further deployment of ITS technologies. Moreover, these models may be used in simulation-assignment tools to evaluate network performance under real-time traveler information and traffic control strategies.

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DYNAMICS OF URBAN COMMUTER BEHAVIOR UNDER REAL-TIME TRAFFIC INFORMATION

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Research Report SWUTC/99/472840-00066-1

SWUTC Project: User Behavior Considerations
in the Provision of Real-Time Information

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DISCLAIMER

EXECUTIVE SUMMARY

The effectiveness of Advanced Traveler Information System (ATIS) technologies in enhancing the quality of life in congested urban and suburban areas critically depends on drivers' responses to these systems and to the information capabilities that they offer. Due to limited real-world implementation of ATIS technologies, it has been especially impractical for researchers to evaluate how real-time information availability influences driver behavior. As decisions about the configuration and deployment of such potentially expensive technologies come under consideration, it is essential to develop the body of fundamental knowledge on driver decision-making processes under the provision of real-time information.

Three main objectives have been achieved in this research. The first main objective is to design interactive experiments to observe commuters' pre-trip path and departure time choice decisions and en-route route diversion decisions over time, and to develop a special-purpose interactive travel simulator for conducting these experiments as well as data collection. To this end, a novel research methodology to study the dynamics of commuter behavior in response to different information strategies of varying information quality in a large-scale interactive laboratory-like setting that is internally and externally consistent with real-world traffic conditions has been designed. Furthermore, a dynamic interactive simulator with the capability for real-time interaction with and among multiple driver participants in a traffic network under different ATIS strategies has been developed.

The second main objective is to conduct the laboratory experiments using the simulator developed and to collect data from which the observational basis could be provided for the development of user response models that could be used in simulation-assignment tools to evaluate network performance under real-time information. The last main objective is to formulate behavioral frameworks of driver response under the provision of real-time traffic information and to build behaviorally realistic decision process models based on the data gathered from the experiments. Theoretical constructs have been developed for representing commuter behavior with regard to (i) compliance to, as well as satisfaction with, the real-time traffic information system and the related trip-making experience, (ii) describing commuters' departure time, pre-trip route and en-route path switching decisions behavior under real-time information, and (iii) capturing day-to-day learning and travel time prediction processes of commuters in response to actual experience and exogenous information. Mathematical models of these processes have been developed and calibrated using the data obtained from the

experiments. These models form an essential component for use within evaluation frameworks (e.g., simulation-assignment models) for assessing the effectiveness of different real-time information strategies.

The dynamic travel simulator developed in this study offers the capability for real-time interaction with and among multiple driver participants in a traffic network under different ATIS strategies. This simulator allows several drivers to "drive" through the network while responding to real-time traffic information, interact with other drivers and contribute to system evolution. Its "engine" is a traffic flow simulator and ATIS information generator that display information consistent with the processes actually taking place in the (simulated) traffic system. The decisions made by the driver participants are feed directly to the simulator, and as such influence the traffic system itself and the subsequent stream of information stimuli provided to the participants.

Using this simulator, a series of interactive experiments have been conducted to examine commuters' trip-making behavior in response to different information strategies of varying information quality. Four important aspects of tripmaker were investigated:

(1) Compliance behavior of ATIS users. The key factors that influence traveler compliance decisions under real-time information were investigated. Models of user compliance to information received were calibrated. This experiment aimed to investigate the association between switching decisions and compliance decisions and to determine how the accuracy and reliability of supplied information to the users affect the overall compliance rate.

(2) ATIS user satisfaction. The objective was to develop a user satisfaction model that represented the level of satisfaction of tripmakers in achieving their commuting purposes under real-time information. This objective was focused on understanding how tripmakers' day-to-day decision-making process might evolve over time as they become more familiar with the real-time information and the traffic system. In particular, this experiment attempted to relate the number of switching decisions made by commuters per trip to information quality and schedule delay as well as to explore any trends of convergence to a satisfactory trip plan.

(3) Trip-making behavior of users under different ATIS strategies. The objective was to investigate how different potential ATIS information strategies, covering a wide range of information quality, affect commuter travel decisions. In this regard, the following three aspects of ATIS information strategies were examined in this experiment:

(i) Nature of information: prescriptive; descriptive.

(ii) Information quality (trip time information based on): reliable prediction; prevailing condition; perturbed prediction; differential predicted; differential prevailing; random.

(iii) Feedback: own trip experience; recommended; actual best.

(4) Dynamic switching models of ATIS users. The objective was to investigate to what extend and how ATIS information quality influence tripmakers' pre-trip and en-route choice behavior. This experiment followed the discrete choice modeling framework developed by Mahmassani and Liu (1997) to compare and validate the role that travelers' own past experience with the traffic information system played in their decision making process, and the interaction effects between travelers' own past experiences and real-time traffic information system. Under this framework, indifference bands for switching decisions in response to different information strategies were calibrated and the results were assessed comparatively.

From the model calibration results, several substantive conclusions have been suggested regarding these behavioral processes. Among these conclusions, we note the following:

(1) The accuracy of the real-time information too was a significant variable that influenced commuters' compliance with route choice information. The commuters were less inclined to comply with real-time information when the system provided under-estimated or over-estimated trip times.

(2) A lower rate of compliance was likely to be achieved under real-time information if commuters recently experienced significant congestion, such as getting stuck in traffic in the preceding highway segment. Similarly, compliance was less likely when commuters experienced high schedule delays (i.e., difference between the "predicted" arrival time and individual preferred arrival time). Furthermore, they were less likely to be compliant when they experienced late arrival to work than when they experienced early arrival to work.

(3) Commuters tended to comply more with real-time information when no switching was required, i.e., when the current path was indeed the path suggested/recommended by the system. A much lesser compliance was likely to be achieved in situations where switching from the current path was required to follow the "best" path. This aversion to switch, when instrumented as a "cost" of switching, was found to be a particularly strong factor.

(4) A higher rate of compliance was likely when commuters were provided with prescriptive or normative information than when they were provided with descriptive information. Likewise, commuters were more inclined to be "satisfied" under the real-time information when supplied with prescriptive information than with descriptive information.

(5) The type of post-trip feedback made available to commuters influenced their behavior of compliance and satisfaction. ATIS systems providing feedback with either the recommended path or the actual best path were more likely to induce a higher rate of user compliance and satisfaction than systems with feedback on own experience only. Tripmakers receiving feedback with the actual best path tended to comply more than those receiving feedback with the path recommended by the system. Tripmakers receiving feedback with the path recommended by the system tended to be less content than those receiving feedback with the actual best path *ex post facto*. Commuters were least prone to comply or be satisfied when the only feedback available was their own experience.

(6) The reliability of the real-time information was a significant variable that influenced commuters' pre-trip departure time and route switching decisions as well as en-route path switching decision. The commuters tended to keep their routine departure time, but change their routes both pre-trip and en-route in response to low reliability of the real-time information system perceived by the commuters. Moreover, tripmakers became more prone to switch routes when the system provided under-estimated trip time information than when the system provided over-estimated trip times. Compared to the findings obtained from previous studies of commuter behavior without real-time information, the experimental results suggested that real-time information availability tended to induce greater frequency of route switching, both pre-trip and en-route.

ABSTRACT

The effectiveness of Intelligent Transportation Systems (ITS) technologies in enhancing the quality of life in congested urban and suburban areas critically depends on drivers' response to these systems and to the information capabilities that they offer. In particular, Advanced Traveler Information Systems (ATIS) aim to improve network flow conditions through the provision of real-time information to drivers, at the trip origin as well as en route. As decisions about the configuration and deployment of such potentially expensive technologies come under consideration, it is essential to develop the body of fundamental knowledge on driver decision-making processes under real-time information supply strategies. This report is structured as a behavioral research effort to examine the processes underlying commuter decisions on en-route route diversions and day-to-day departure time and route choices as influenced by the provision of real-time traffic information.

This report presents a series of large-scale laboratory-like experiments in which real commuters interact with and among multiple participants in a traffic network in real-time under various information strategies through a dynamic travel simulator. This simulator considers both the supply-side system performance as influenced by driver response to real-time traffic information as well as the demand-side driver behavior as influenced by real-time traffic information based on system performance. Its "engine" is a traffic flow simulator and ATIS information generator. By actually simulating traffic conditions in response to the supplied commuter decisions, the simulator provides stimuli to the participants that are always consistent with physically realistic traffic behavior, and with their previous actions.

The data collected from these experiments form the observational basis for the development and calibration of Poisson event count models of user compliance and satisfaction behavior as well as multinomial probit models of dynamic departure time and route switching decisions. By estimating these models, substantive conclusions regarding the factors influencing the commuter behavior in response to various ATIS systems are obtained, addressing key fundamental issues critical to the further deployment of ITS technologies. Moreover, these models may be used in simulation-assignment tools to evaluate network performance under real-time traveler information and traffic control strategies.

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CHAPTER 1: INTRODUCTION

MOTIVATION

Rapid growth in automobile use has out-paced infrastructure investment, creating disruptive levels of traffic congestion. In the United States alone, congestion accounts for over 2 billion vehicle hours of delay on urban freeways and up to $100 billion of productivity losses annually, not to mention that the high use of automobiles results in tens of thousands of accidents and fatalities each year (United States General Accounting Office, 1991). While additional construction is inevitable, more efficient use of the current transportation network via the implementation of Intelligent Transportation Systems (ITS), formerly Intelligent Vehicle-Highway Systems (IVHS), is crucial.

Various efforts have been initiated worldwide for the development of ITS systems. Major demonstration projects and research programs can be found in the United States, Europe, Japan, and Australia (Booze•Allen and Hamilton, 1998; Catling and McQueen, 1991; Kawashima, 1991). There are three general clusters of ITS technologies with application to commuter mobility: Advanced Traffic Management Systems (ATMS), Advanced Traveler Information Systems (ATIS), and Advanced Vehicle Control Systems (AVCS). Essentially, ITS use advanced information processing and communications technologies to manage traffic and advise drivers, and eventually control the flow of vehicles to achieve improvements in efficiency and safety.

ATIS is especially targeted to assist drivers in trip planning and decision making on destination selection, departure time and route choices, congestion avoidance, and navigation, to improve the convenience and efficiency of travel (Mobility 2000, 1990; Rillings and Betsold, 1991). Various ATIS classes have been defined from Class 0 static, open loop systems, to Class 4 dynamic, closed-loop systems, enabling two-way communication between the vehicle and the traffic control center (OECD, 1988).

Technological development to-date relating to communications use for system-level control through the provision of information to individual drivers has proceeded essentially without guidance on several key elements and phenomena that can have a determining effect on the ultimate performance of these technologies, including: the nature and amount of the information provided to individual drivers; the behavioral processes governing the response of the users who receive information; the system-wide implications of different information supply strategies; and the appropriate objectives for the central controller.

The effectiveness of ATIS technologies in enhancing the quality of life in congested urban and suburban areas critically depends on drivers' responses to these systems and to the information capabilities that they offer. Due to limited real-world implementation of ATIS

technologies, it has been especially impractical for researchers to evaluate how real-time information availability influences driver behavior. As decisions about the configuration and deployment of such potentially expensive technologies come under consideration, it is essential to develop the body of fundamental knowledge on driver decision-making processes under the provision of real-time information.

Driver behavior and response to real-time traffic information systems is the result of a complex process involving human judgment, learning and decision-making in a dynamic environment. Uncertainty in this dynamic environment originates from the fact that: 1) the consequences of an individual driver's decision depends on the decisions of other drivers in the network, and 2) the interactions which determine these outcomes take place in the traffic system and are highly nonlinear. In particular, a "recommended" path predicated on current link trip times may turn out to be less than optimal as congestion in the system evolves. Hence, the accuracy of the information provided to participating drivers and the resulting reliability of this information as a basis for route choice decisions are governed by the dynamic nature of the driver-decision environment and the presence of collective effects in the network as a result of the interactions of a large number of individual decisions (Mahmassani and Chen, 1991; Mahmassani and Chen, 1993). Consequently, driver decisions on the acquisition of the information system and compliance with its instructions are influenced by the user perceptions of the reliability and usefulness of the system, formed mostly by learning through one's own experience with the system, as well as reports by friends, colleagues, and popular media. This is a long-term process that depends on the type and nature of the information provided, in addition to the individual characteristics and preferences of the driver. Furthermore, the interactions among drivers with access to the same kind of traffic information cannot be ignored at high market penetration levels.

The ideal way to study this process is through observations of actual driver decisions in real-world systems. However, as noted earlier, in the absence of sufficient deployment of the technologies of interest, it is practically difficult to obtain real-world data on the actual behavior of drivers under different real-time information strategies, on a daily basis, together with the various performance measures affecting these responses.

Several methodological approaches have been proposed for assessing the effectiveness of various possible forms of ATIS in reducing recurrent and non-recurrent traffic congestion and examining the interactions among key parameters, such as nature and amount of information displayed, market penetration, and congestion severity (Mahmassani and Jayakrishnan, 1991; Mahmassani and Chen, 1991; Tsuji et al., 1985; LeBlanc, 1989; Koutsopoulos and Lotan, 1990). Furthermore, various human factors studies have been carried out concerning the attentional demand requirements of in-vehicle navigation devices and their effects on the safety of driver

performance, using either a driving simulator or specially adapted vehicles in real urban environments (Dingus et al., 1989; Parkes, Ashby, and Fairclough, 1991; Walker et al., 1990). Mail-back surveys and telephone interviews on drivers' willingness to divert en route in response to real-time traffic information and their preferences towards the different features of these systems have also been conducted (Shirazi, Anderson, and Stesney, 1988; Haselkorn, Spyridakis, and Barfield, 1991; Khattak, Schofer, and Koppelman, 1991; Khattak, Koppelman, and Schofer, 1993).

Eight computer-based interactive simulators have been developed to study different aspects of commuter behavior through laboratory experiments as an alternative and precursor to real-world applications. They are discussed hereinafter, following their approximate chronological order of development. IGOR (Interactive Guidance on Routes) and VLADIMIR were developed by Bonsall et al. for investigating factors affecting drivers' compliance with route guidance advice, such as quality of advice and familiarity with the network (Bonsall and Perry, 1991; Bonsall, Clarke, Firmin, and Palmer, 1995). Chen and Mahmassani developed a dynamic travel simulator, using DYNASMART, a special-purpose traffic simulation and path assignment model, to create a dynamic simulated traffic system and to generate real-time information as traffic evolves (Chen and Mahmassani, 1993). This simulator was developed as part of this research project, specifically designed to conduct behavior experiments for the study of day-to-day dynamics of tripmaker behavior under real-time information. Allen et al. used an interactive simulator to study the impacts of different information systems on drivers' route diversion and alternative route selection (Allen et al., 1991a). In order to enable human factors research, the TNO Institute for Human Factors used a fixed-base mock-up vehicle simulator to assess the effects of variable message signs on driver behavior (Van der Mede and Van Berkum, 1991). The driving tasks were simulated using this vehicle simulator with controls such as steering wheel, pedals, etc. FASTCARS (Freeway and Arterial Street Traffic Conflict Arousal and Resolution Simulator), developed by Adler et al., was used to predict en-route driver behavior in response to real-time traffic condition information, based on conflict assessment and resolution theories (Adler, Recker, and McNally, 1994). The purpose of the simulator developed by Vaughn et al. was to collect pre-trip route choice data under the influence of ATIS for a two parallel-facility corridor (Vaughn et al., 1993; Yang et al., 1993). Lastly, Koutsopoulos et al. developed a driving simulator for the collection of data in order to construct models on driver's route choice behavior in the presence of information (Koutsopoulos et al., 1994).

All the simulators to date, with the exception of Chen and Mahmassani's dynamic travel simulator, are either deterministic, with all traffic conditions and consequences of driver actions predetermined and no consideration of network-wide traffic characteristics, or stochastic, in the

sense that link travel times are selected from some probabilistic distributions. These simulators can only interact with one subject at any given time, ignoring interactions among drivers in the same traffic system. As such, they have ignored the interactions among drivers with access to different kinds of traffic information or guidance devices in the same traffic system. Most simulators provide different preset levels of information quality to the experimental subject, in an arranged sequence. In addition, the effect of the drivers' responses to the information on the traffic system is not considered. Allen et al., TNO and Adler et al.'s simulators assume the information supplied to be perfect and static, which is not representative of actual real-time ATIS environments.

Controlled "laboratory-like" interactive experiment involving real commuters in a simulated traffic system has been conducted investigating the travel behavior of commuters over time in response to different real-time information strategies of varying information quality and credibility. Following Mahmassani and Herman's work on interactive experiments for the study of day-to-day dynamics of tripmaker behavior (Mahmassani and Herman, 1990), this experiment involved commuters supplying departure time and route decisions in response to displayed traffic condition information in a simulated traffic system, using Chen and Mahmassani's interactive dynamic multi-user computer-based simulator. By actually simulating traffic conditions in response to the supplied commuter decisions, the simulator provides stimuli to the participants that are always consistent with physically realistic traffic behavior, and with their previous actions. Such experiment could play an important transitional role in gaining fundamental insights into behavioral phenomena that would play a key role in determining the effectiveness of ATIS and ATMS strategies.

Two classes of mathematical models have been employed to analyze commuter trip-making behavior and capture the effects of the characteristics of the information strategies, the traffic system, and the commuters on this behavior: (1) event count models of the observed frequency of decisions (Poisson regression models) have been estimated to capture the principal effects of the commuters' experience with the traffic system and with the real-time information on user compliance and satisfaction behavior; and (2) dynamic models of discrete choices (multinomial probit models) including pre-trip departure time and path decisions as well as en-route route switching choices are calibrated. By estimating these behavioral models using the experimental data, substantive hypotheses regarding the factors influencing the commuter behavior in response to different real-time information strategies of varying information quality and credibility have been tested. These calibrated behavioral models furnish guidelines for the design of ATIS systems as well as provide an essential component of ATIS evaluation frameworks (such as

simulation-assignment models), to ensure that any ATIS design and development process leads to an effective and satisfactory product.

RESEARCH OBJECTIVES

This paper presents a dynamic travel simulator that offers the capability for real-time interaction with and among multiple driver participants in a traffic network under different ATIS strategies. This simulator allows several drivers to "drive" through the network while respond to real-time traffic information, interact with other drivers and contribute to system evolution. It considers both the supply-side system performance as influenced by driver response to real-time traffic information and the demand-side driver behavior as influenced by real-time traffic information based on system performance. Other simulators reviewed earlier are primarily computer-based devices for the display of pre-determined stimuli and elicitation and collection of the participants' responses. The simulator described here actually "simulates" traffic. Its "engine" is a traffic flow simulator and ATIS information generator, that displays information consistent with the processes actually taking place in the (simulated) traffic system under the particular information supply strategy of interest. The decisions made by the driver participants are fed directly to the simulator, and as such influence the traffic system itself and the subsequent stream of information stimuli provided to the participants.

In addition to studying user response to ATIS information for a particular commute on a given day, this simulator allows the investigation of the day-to-day evolution of individual decisions under such information strategies. This longer-term dimension is missing from most available studies of the effectiveness of real-time information systems. Our experiments consider system evolution and possible equilibration by including the participants and the performance simulator in a loop whereby tripmakers may revise their decisions from one iteration day to the next. These experiments are intended to investigate both the real-time and day-to-day dynamic properties of traffic networks under real-time information, particularly issues of convergence to an equilibrium, stability and benefits following shifts in user trip timing decisions.

The context for this research is that of morning peak-period commuters in congested traffic corridors. In the interactive experiment, each subject is asked to "drive" a vehicle to the Central Business District (CBD) through a corridor network. Each subject is provided with real-time traffic information before each trip on the basis of which he/she independently supplies his/her path and departure time decisions. These decisions are in turn fed into a traffic simulation and path assignment model. Each subject's vehicle is then moved along the selected path according to the prevailing traffic condition on the link that the vehicle is on. At each junction where the subject has the opportunity to switch to an alternative route, he/she is again provided with real-time traffic information and asked to decide whether to stay on the current path or switch to an

alternative route. Feedback is supplied to the subject at the end of the trip on the consequences of his/her decisions. At the end of each trip, new departure times are sought from all subjects for the next day's trip.

The main research objectives are:

(1) to formulate behavioral frameworks of driver response under the provision of real-time traffic information,

(2) to design interactive experiments to observe commuters' pre-trip path and departure time choice decisions and en-route route diversion decisions over time in a controlled environment.

(3) to develop a special-purpose interactive travel simulator for data collection,

(4) to conduct laboratory experiments using the simulator developed, and to build behaviorally realistic decision process models based on the data gathered from the experiments.

The interactive experiment has been designed to examine commuters' trip-making behavior in response to different information strategies of varying information quality and credibility. It investigates the investigate the effect of these strategies on the behavior of user compliance to the information supplied as it is critical to the successful deployment of the information technology in achieving traffic control objectives, as well as the behavior of overall user satisfaction over time as they become more familiar with the traffic system and the information received. In addition, commuters' day-to-day departure time and route decision processes under these strategies are analyzed, following the modeling framework developed by Mahmassani and Liu (1997). Four important aspects of tripmaker behavior in response to real-time traffic information are investigated in this experiment:

(1) Compliance behavior of ATIS users. The key factors that influence traveler compliance decisions under real-time information are investigated. While most existing route choice models might explain trip-making behavior under real-time information adequately, models of user compliance to information received could be more applicable in determining the effectiveness of real-time information provision in achieving traffic management objectives. This experiment aims to investigate the association between switching decisions and compliance decisions and to determine how the accuracy and reliability of supplied information to the users affect the overall compliance rate.

(2) ATIS user satisfaction. The objective is to develop a user satisfaction model that could represent the level of satisfaction of tripmakers in achieving their commuting purposes under real-time information. The authors are interested in understanding how tripmakers' day-to-day decision-making process might evolve over time as they become more familiar with the real-time information and the traffic system. In particular, this experiment attempts to relate the number of switching decisions made by commuters per trip to information quality and schedule delay as well as to explore any trends of convergence into a satisfactory trip plan in which no switches are desirable under a recurring traffic condition. This proposed trend of diminishing propensity to switch either

departure time or route has especially meaningful implications to the longer term effects of ATIS on the evolution of traffic system and travel demand.

(3) Trip-making behavior of users under different ATIS strategies. The objective here is to investigate how different potential ATIS information strategies, covering a wide range of information quality and credibility, affect commuter travel decisions. In this regard, the following three aspects of ATIS information strategies are examined in this experiment:

   (a) Nature of information: prescriptive; descriptive.

   (b) Information quality (trip time information based on): reliable prediction; prevailing condition; perturbed prediction; differential predicted; differential prevailing; random.

   (c) Feedback: own trip experience; recommended; actual best.

A detailed discussion of these factors can be found in the experimental design section of Chapter 3. Of principal interest here is to investigate the possible existence of an intrinsic hierarchy of trip-making behavior in accordance with a classification of the above-mentioned aspects of ATIS information. The conclusions from such investigation are of particular interest to the real-time information providers/traffic controllers in meeting their goals.

(4) Dynamic switching models of ATIS users. The objective is to investigate to what extend and how ATIS information quality and credibility influence tripmakers' pre-trip and en-route choice behavior. This experiment follows the discrete choice modeling framework developed by Mahmassani and Liu (1997) to compare and validate the role that travelers' own past experience with the traffic information system plays in their decision making process, and the interaction effects between travelers' own past experiences and real-time traffic information system. Under this framework, indifference bands for switching decisions in response to different information strategies are calibrated and the results assessed comparatively.

RESEARCH SIGNIFICANCE AND CONTRIBUTIONS

One of the principal determinants of the effectiveness of real-time traffic information systems is the user's response to this information, both in real-time and over the long run. The available body of knowledge in this area is very limited, and will remain rather speculative until a meaningful observational basis has been developed. Laboratory-like experiments of the type described in this report provide a low-cost alternative for a much needed start on acquiring observations of actual tripmakers. Three unique features of the experimental apparatus and procedures described in this report should be emphasized: (1) the stimuli provided to the participants are generated by a traffic simulation model, and are therefore both internally and externally consistent with real-world traffic conditions, (2) the interactive multi-user capability introduces greater realism, especially at higher market penetration levels, and (3) the day-to-day

aspect of the experiments addresses an essential question that has often been ignored in discussions of ATIS effectiveness.

The kind of data that are obtained from such controlled conditions can provide a basis for the development of user response models that may be used in simulation-assignment tools to evaluate network performance under real-time information. It should be noted that the richness of this data and the dynamic interactive nature of its source raises challenging methodological questions in terms of analysis, particularly model specification and parameter estimation. It is therefore necessary to advance the state-of-the-art methodologically in order to take advantage of such data and properly address the behavioral questions of interest. Naturally, simulators and laboratory-like experiments of the type described are not intended to totally replace actual field demonstrations and tests. Their role is to provide a relatively low cost and rapid test bed to address key fundamental issues that are critical to the further development and deployment of ITS technologies. Insights gained from such experiments can then guide the cost-effective development of full-scale field tests.

The principal contributions of this research are listed as follows:

A theoretical construct for representing commuter behavior with regard to (i) representing commuters' compliance to as well as satisfaction with the real-time traffic information system and the related trip-making experience, (ii) describing commuters' departure time, pre-trip route and en-route path switching decisions behavior under real-time information, and (ii) capturing day-to-day learning and travel time prediction processes of commuters in response to actual experience and exogenous information.

A novel research methodology to study the dynamics of commuter behavior in response to different information strategies of varying information quality and credibility in a large-scale interactive laboratory-like setting, that is internally and externally consistent with real-world traffic conditions.

A dynamic interactive simulator with the capability for real-time interaction with and among multiple driver participants in a traffic network under different ATIS strategies. It considers both the supply-side system performance as influenced by driver response to real-time traffic information and the demand-side driver behavior as influenced by real-time traffic information based on system performance.

Actual commuter travel behavior data collected from laboratory-like experiment using the dynamic interactive simulator. This provides an observational basis for the development and calibration of pertinent behavioral models of interest in the study of commuter decision dynamics under ATIS.

Models of ATIS user response to different information strategies in the areas of: (i) user compliance, (ii) user satisfaction, and (iii) user joint departure and route switching decisions. These models form an essential component for use within evaluation frameworks (e.g., simulation-assignment models) intended to assess the effectiveness of different real-time information strategies.

STRUCTURE AND OVERVIEW OF REPORT

First, the introduction chapter gives an overview of the problem definition and motivation, as well as research objectives, significance and contributions. A background review of relevant work under ATIS is presented in chapter two. General behavioral considerations for the user response models are discussed first, followed by a comprehensive analysis of driver cognitive tasks and implications for ATIS. A survey of recent ATIS behavior research and real-world implementations is provided next. In the third chapter, the research methodology for this research is described, starting with a synthesis of previous, directly related research experience. A presentation of the dynamic interactive simulator is provided next, followed by the details of the laboratory experiment. Theoretical frameworks for models of user compliance, satisfaction, and departure time and path switching are described in chapter four, including model limitations and estimation challenges. Detailed estimation results of these ATIS user behavior models are presented in chapter five. The last chapter concludes with a summary and conclusions from this study as well as implications and guidelines for ATIS developers and system operators. Directions for future research are proposed last.

CHAPTER 2: BACKGROUND

INTRODUCTION

This chapter presents a review and discussion of developments that have taken place over the past few decades in the area of modeling traveler behavior and response to information, with particular focus on one aspect of the dynamics of the transportation systems – Advanced Traveler Information Systems (ATIS).

In recent decades, there has been a paradigmatic shift in transportation needs, with driver decision making and behavior receiving much attention and complementing the network and system oriented research that focused on facility modification or new construction. In this approach, demand side modeling has dominated and several travel behavior models based on various logit and stochastic formats have been proposed and tested, many of them with considerable success. Recent reviews can be found in Stopher and Le-Gosselin (1997) and Bhat (1997).

The goal of demand-side models is to better distribute traffic both spatially and temporally on the existing road network, with increasing emphasis has been placed on telecommuting, peak-period traffic control, flexible work hours, and an increasing interest in the in-vehicle reception and use of ATIS. These are designed to facilitate mobility through existing systems by: (1) reducing travel demand through suppression and selective elimination of trips; (2) targeting single occupant vehicles in peak hours, and curtailing traffic volume on key links during these periods; (3) spreading peak by allowing travel demand shifts temporally; and (4) relieving driver stress and frustration as well as assisting them in making informed trip-making decisions through the provision of timely pre-trip or en-route information about congestion, disruptions, and accidents, resulting in more efficient flow of traffic.

Of particular relevance to this paradigm shift are research efforts in the area of modeling commuter decisions in departure time and route choices, day-to-day dynamics of these decisions in interaction with system performance, and the role of information. Because of the inherent complexity of gathering and subsequently analyzing observations of this dynamic phenomena, new measurement instruments, data, and travel behavior models are required.

This chapter provides a review and discussion of background material pertaining to the investigation of traveler behavior in response to real-time information. First, a synthesis of the measurement instruments for, and information resources of, travel behavior research are provided, including past research on traveler behavior characteristics and decision-making processes related to predicting user's responses to ATIS. General ATIS behavioral considerations are then discussed, covering different classes of information strategies and their associated choice dimensions. Sixteen past and on-going ATIS operational field tests implemented in the US, providing a connection between research, development and full scale deployment of ATIS technologies, are presented. Finally, a summary of the chapter is given.

MEASUREMENT INSTRUMENTS FOR AND INFORMATION SOURCES OF TRAVELER BEHAVIOR RESEARCH

The field of travel behavior measurement has been active in one form or another for about fifty years. Different methods of collecting information about travel behavior have been explored during that time. Questionnaire surveys distributed at selected places along routes provided the first comprehensive databases for the Chicago Area Transportation Study (CATS), Pittsburgh Area Transportation Study (PATS), and many others. These in-car, on-the-spot, or mail-back surveys collected data on personal and family characteristics of drivers and passengers, demographics, trip types, mode of travel, trip purpose, and trip frequency. Surveys of this kind have become more robust and comprehensive as survey research itself has become more of a procedural science and sampling methods have become more established.

While mechanized traffic counts continues to furnish a measure of cumulative vehicular movements at specific locations within a transportation network, surveys have become the dominant means for providing information about travelers' preferences and characteristics, route and departure time decision processes, destination choice, and so on, all of which provide the bases of much of the data collected about travel behavior and activities to date (Brog et al., 1985).

Detailed travel diaries kept by a specially targeted sample group and focused on a specific aspects of urban travel (for example, commuting, shopping, cultural or recreational activities, and so on) became popular in the early eighties. A comprehensive overview of these approaches was given in Ampt, Richardson, and Brog (1985), providing an important reference source for collection of detailed transportation data. For example, Mahmassani, Joseph, and Jou (1993) investigated the day-to-day dynamics of driver behavior in a commuting context using a two-stage survey of trip-making decisions in the North Dallas corridor. This involved first distributing a short questionnaire to 13,000 households in the selected area, followed by a more detailed activity diary for a selected portion of this sample which was for recording commuting trips to work and returning to home. Data were also collected on trip chaining, departure time and route choice. Such two-stage procedures have proven to be reliable, valid and cost-effective ways of collecting large quantities of data.

With the emphasis in studying travel demand from an activity-based perspective, Brog and Erl (1981) has suggested that an understanding of the underlying tripmakers' decision-making processes is necessary. This is an immoderate shift from the traditional transportation planning "four-stage procedure" where statistical associations, rather than human behavioral relationships, were the principal concerns. This innovative approach to model travel demand as an derived demand has provided a different kind of transportation data, such as driver perceptions, attitudes, and preferences, complementing the existing revealed preference and statistical estimation methods (Stopher and Lee-Gosselin, 1997).

Research work emphasizing on the travel behavioral changes and decision dynamics capturing driver decision making and choice behavior in response to changes in travel environment have also taken shape, along with the developments in the activity-based arena. These changes in behavior cover a variety of travel choice dimensions ranging from switching between drive-alone and car-pooling to changing destinations, routes, or time scale at which

activities are undertaken. Additional travel behavior features that have come under investigation include trip chaining and scheduling of activities over a time span rather than a single time. It was during this time that transportation researchers began to develop special-purpose computer simulation models and used them to conduct interactive experiments involving actual commuters, in an effort to study tripmaker behavior dynamics (Mahmassani and Herman, 1990), the results of which were a significant number of dynamic models of traveler responses. Computational process models have also been developed by primarily geographers, planning professionals, and social scientists, capable of relating elements of real and cognized environments with factors affecting travel choices (Miller, 1991; Axhausen and Garling, 1992). While much of these work still rely on utility maximization assumptions, boundedly-rational or satisficing behavior has been found to better represent tripmaker choice dynamics (Mahmassani and Chang, 1987; Mahmassani and Stephan, 1988; Mahmassani and Jou, 1996).

Along with the advent of ITS, formerly IVHS, a number of research efforts have been focusing on evaluating the potential benefits of various aspects of these systems. Of particular interest is in the area of ATIS, the effectiveness of which in enhancing the quality of life in congested urban and suburban areas critically depends on drivers' responses to these systems and to the information capabilities that they offer. Due to the limited implementation of actual ATIS systems in the real world, most of the research in this area have concentrated on simulation-based interactive experiments rather than gaining experience in the field. This type of laboratory procedure using driver simulators differ from the more classic revealed preference studies in that, while the revealed preference methods elicit answers to questions regarding some hypothetical technologies yet to be available, subjects in the driving simulation environment actually experience various scenarios involving different kinds of technology-based stimuli. In the latter case, the subjects choices and decision-making processes are revealed by the consequent actions they take.

Eight computer-based interactive simulators have been developed to study different aspects of commuter behavior through laboratory experiments to date. IGOR (Interactive Guidance on Routes) was among the first interactive simulators developed for investigating factors affecting drivers' compliance with route guidance advice, such as quality of advice and familiarity with the network (Bonsall and Perry, 1991). The results of this study conducted by the University of Leeds suggested that information quality, familiarity of the network and local traffic conditions are the key determinants. More recently, the same development team launched a new simulator, VLADIMIR, for studying drivers' route choice behavior in response to different types of ATIS (Bonsall, Clarke, Firmin, and Palmer, 1995). This simulator has a more sophisticated representation of the network using digitized photographs to represent real-world traffic conditions. The effectiveness of providing variable message signs (VMS) was examined through studies using VLADIMIR in Scotland and Denmark, the results of which indicated that among others, the clarity of the message, the distance between the VMS and the location of incident, and the information on expected delay tend to influence drivers' diversion decision the most (Bonsall and Palmer, 1995).

Chen and Mahmassani (1993) developed a dynamic travel simulator, integrating DYNASMART, a dynamic traffic simulation model, and a specially design multiple-user interface to create a dynamic simulated traffic system and allow a substantial number of driver subjects to participate in it simultaneously. This simulator generates real-time advisory information as traffic evolves and has the capability to study the day-to-day evolution of user decisions in response to real-time information, in addition to within-day and real-time travel choice dynamics. Chen and Mahmassani's dynamic travel simulator is unique in several ways: (1) it allows several drivers to "drive" through the network while respond to real-time traffic information, interact with other drivers and contribute to system evolution; (2) it considers both the supply-side system performance as influenced by driver response to real-time traffic information and the demand-side driver behavior as influenced by real-time traffic information based on system performance; (3) in addition to studying user response to ATIS information for a particular commute on a given day, this simulator allows the investigation of the day-to-day evolution of individual decisions under such information strategies; and (4) it considers system evolution and possible equilibration by including the participants and the performance simulator in a loop whereby tripmakers may revise their decisions from one iteration day to the next. This simulator is intended to investigate both the real-time and day-to-day dynamic properties of traffic networks under real-time information, particularly issues of convergence to an equilibrium, stability and benefits following shifts in user trip timing decisions. Data obtained using this simulator provide the observational basis for the modeling work. Readers are referred to Chapter 3 for a detailed discussion of Chen and Mahmassani's dynamic travel simulator.

Allen et al. (1991a; 1991b) used an interactive simulator to study the impacts of different information systems on drivers' route diversion and alternative route selection. This simulator controls a series of situational slides as well as the associated auditory feedback during the laboratory sessions. Older drivers were found to be more hesitant to divert than younger drivers in this study. In order to enable human factors research, the TNO Institute for Human Factors used a fixed-base mock-up vehicle simulator to assess the effects of variable message signs on driver behavior (Van der Mede and Van Berkum, 1991). The driving tasks were simulated using this vehicle simulator with controls such as steering wheel, pedals, etc.

FASTCARS (Freeway and Arterial Street Traffic Conflict Arousal and Resolution Simulator), developed at the University of California at Irvine, was used to gather data for estimating and calibrating predictive models of en-route driver behavior in response to real-time traffic condition information, based on conflict assessment and resolution theories (Adler, Recker, and McNally, 1994; Adler and McNally, 1994). This PC-based simulator was used to capture driver route choice decisions in response to three types of ATIS technologies, namely, VMS, highway advisory radio (HAR), and in-vehicle navigation systems (IVNS). Travel takes place on a link-by-link basis, ignoring system-wide traffic and focusing on traffic around the driver. Several significant factors were found by Adler et al., including perceived travel speed, average link speed, experience with the paths taken, and road type. They have also found a higher preference towards HAR to IVNS, though route guidance information was found to be a key factor in route decisions of drivers with lower familiarity profiles.

The purpose of the simulator developed by Vaughn et al. at the University of California at Davis was to collect pre-trip route choice data under the influence of ATIS for parallel-facility corridors (Vaughn et al., 1993; Vaughn et al., 1995; Yang et al., 1993). Among their findings, individual characteristics were found to be the major variables in test subjects' choice of information acquisition as well as travel decisions. Koutsopoulos et al. (1994) developed a driving simulator for the collection of data in order to construct models on driver's route choice behavior in the presence of information. This model, developed at Massachusetts Institute of Technology, were similar to IGOR, but with much enhanced user interface capabilities. They modeled congestion, incidents, and information availability as three key factors in driver route choice behavior.

All the simulators, with the exception of Chen and Mahmassani's dynamic travel simulator, are either deterministic, with all traffic conditions and consequences of driver actions predetermined and no consideration of network-wide traffic characteristics, or stochastic, in the sense that link travel times are selected from some probabilistic distributions. These simulators can only interact with one subject at any given time, ignoring interactions among drivers in the same traffic system. As such, they have ignored the interactions among drivers with access to different kinds of traffic information or guidance devices in the same traffic system. Most simulators provide different preset levels of information quality to the experimental subject, in an arranged sequence. In addition, the effect of the drivers' responses to the information on the traffic system is not considered. Allen et al., TNO and Adler et al.'s simulators assume the information supplied to be perfect and static, which is not representative of actual real-time ATIS environments.

GENERAL ATIS BEHAVIORAL CONSIDERATIONS

The effectiveness of information technology to achieve traffic control objectives depends on: (1) the existence of improvement opportunities in prevailing traffic conditions, (2) the nature and type of information available to different segments of the user population, and (3) users' behavior and response to the supplied information.

Mahmassani and Jayakrishnan (1991) have classified information strategies into four generic categories:

(1) Descriptive, stored information, such as a static map that displays only stored information on (fixed- or time-dependent) trip times on the various network links.

(2) Descriptive, real-time information, where the trip times are updated on a real-time basis to indicate prevailing congestion on the various network links.

(3) Descriptive, real-time information with individual optimization, in which the link-level information could be processed either on board or centrally to compute the current shortest path from the present position to the desired destination of given driver.

(4) Controlled guidance, under which the instructions given to users reflect a central controller's system-level objectives, subject to certain constraints to prevent unreasonable penalties to any individual tripmaker.

User behavior and response to the supplied information is the result of a complex process involving human judgment, learning and decision-making in a dynamic environment. This process depends on the type and nature of the information provided, in addition to the individual characteristics and preferences of the tripmaker. In all four cases identified above, user response can be viewed in terms of four choice dimensions: (1) acquisition of the equipment, (2) consultation of the information system, (3) compliance with its instructions, and (4) trip decisions and actions (behavior). Of course, these dimensions take place over varying time frames.

Acquisition of the on-board equipment is a long-term decision, reached by the user after some deliberation involving the trade-off of perceived benefits against monetary costs. This decision can undoubtedly be modeled adequately in a standard random utility maximization discrete choice framework.

Consultation of the equipment is a real-time decision, made along, and possibly also at the beginning of the trip. The consultation decision is likely to be governed by different behavioral mechanisms for each of the above generic types of information systems and strategies. For example, a static map with historic information only (the first strategy) is not likely to be consulted (for path selection purposes) other than at the beginning of a trip or to find an alternate path along the way if actual congestion exceeds anticipated congestion. On the other hand, a controlled guidance system (the fourth strategy) is likely to be consulted on a virtually continuous basis. The underlying behavioral process for the second strategy is likely to be closer to that for the first strategy, whereas the third strategy is likely to be closer to the controlled guidance case. In all cases, the consultation decision is influenced by longer-term processes, particularly user perceptions of the reliability and usefulness of the system, formed mostly by learning through one's own experience with the system, as well as reports by friends, colleagues, and popular media.

The third choice dimension is referred to here as compliance. It is a real-time decision, definitely influenced by the above-mentioned longer-term learning phenomena that form user perceptions. This dimension is not directly applicable to the first two information supply strategies. It is most applicable in the fourth strategy, where specific route guidance instructions are provided, with the controller's intent that they are to be followed by the motorists. In this case, compliance will be a critical factor in overall system effectiveness. For the third strategy, the applicability of this dimension depends on the specific information displayed. If it consists of just (current) trip times on alternate paths, then it is not clear what compliance would refer to. On the other hand, if a single path is displayed, because it has been determined to be the shortest or otherwise "best" according to some criterion (or as a result of an on-board expert system recommendation), then compliance could be defined relative to that recommendation.

The fourth dimension actually includes several possible decisions, with varying time frames for each. The most evident is en-route path switching, which is the principal real-time decision targeted by in-vehicle information systems. A second decision consists of initial (home-based for the AM commute) route selection. This decision can be taken as an immediate response to real-time information consulted at the trip origin (and supplied either through the in-vehicle display or some other in-home medium). However, it is also influenced by the day-to-day experience of the

users in the system, which contributes to forming the users' perceptions both over the short-term (day-to-day) and over a longer time frame. A third response consists of trip timing. From day to day, the tripmaker will adjust his/her departure time, as a result of learning through repeated system usage. The user's preferred arrival time plays an important role in this process. Some equilibrium choices or timing strategies might be reached by individual commuters over time as a result of this process. Over the medium to long term, changes in activity patterns could take place, reflecting the users' potentially improved ability to schedule their activities using reliable real-time information. Of course, over the very long term, the standard choice dimensions of residential and/or work location remain available for users; these are outside the scope of the present discussion.

An important factor that was noted in connection with all of the above decisions is that of the perceived quality of the real-time information and its resulting credibility. This arises primarily from the dynamic nature of the decision environment and the presence of collective effects in the network as a result of the interactions of a large number of individual decisions. In particular, a "best" path predicated on current link trip times may well turn out to be less than optimal as congestion in the system evolves. This issue is of particular concern for the third and fourth information strategies defined above. Of course, it is possible to use predicted trip times for path computations instead of the current actual values. However, the accuracy of the prediction logic would have to be questioned as no such entirely satisfactory prediction techniques are presently available. This is particularly problematic under the fourth strategy (controlled guidance). To what extent will (and can) the anticipated response of users to the supplied guidance instructions be incorporated in the prediction? Naturally, the reliability issue becomes more critical as the fraction of users in the system with access to the information increases.

ATIS FIELD TESTS AND OPERATIONAL EXPERIENCE

Several ATIS field tests of varying scope and size have been operationalized in real-world environments in the United States, Europe, Japan, and Australia. These Field Operational Tests (FOTs), serving as a bridge between research and development (R&D) and full-scale deployment of ITS technologies, are an integral part of the ITS implementation plan. ATIS-related FOTs in the United States are described as follows:

Advanced Driver and Vehicle Advisory Navigation Concept (ADVANCE)

The ADVANCE ITS field FOT demonstrated the use of an in-vehicle advanced traveler information system in the northwest suburbs of Chicago, Illinois. It was designed to provide drivers, familiar with the area in which they were driving, with the fastest route to their destination through an in-vehicle traveler information and route guidance system. The system provided route guidance information using a static database of travel times and dynamic information on traffic conditions. Equipped with this information, a driver could select a route to follow. The driver received Dynamic Route Guidance (DRG) to the selected destination via the selected route.

The operational testing took place between June and December of 1995. It demonstrated the feasibility of using a DRG system to improve travel times under certain conditions. The evaluation of the integrated system of computerized traffic information analysis software, in-

vehicle advisory systems, and a dedicated radio frequency communication system showed that it is possible to collect, analyze, and communicate potentially useful information to users. Another key component of the ADVANCE tests was the use of probe vehicles to collect actual travel times on each link to the Traffic Related Functions (TRF) at the Traffic Information Center (TIC). The data provided by these probes provided a reliable indicator of traffic conditions and could thus be a valuable resource for traffic monitoring and analysis in future ATIS deployments. The test partners were the Federal Highway Administration (FHWA), Illinois Department of Transportation (DOT), Motorola, and the Illinois Universities Transportation Research Consortium. A full report on this FOT can be found in Argonne National Laboratory (1997).

Advanced Rural Transportation Information and Coordination (ARTIC)

The ARTIC ITS Field Operational Test combines the communications dispatch operations of four public service agencies into a single communications center that serves a remote area in the Arrowhead region of northeastern Minnesota. The ARTIC partnership crosses state agency jurisdictions and functions, and foster cooperation between highway and transit interests. This cooperation is critical in remote, rural regions where resources are limited and pooling of assets is necessary to satisfy the operational requirements of multiple agencies.

The project began operations in October 1997. Data collection continued until September 1998. The final evaluation report is anticipated in December 1998. Since the initial operations phase, the use of communications facility is already yielding benefits. Rapid responses to emergencies have been achieved, particular in winter conditions, that would not have been possible prior to system deployment. The participating agencies include Arrowhead Regional Development Commission, Arrowhead Transit, City of Virginia Transit, FHWA, Minnesota DOT, and Minnesota State Patrol.

Atlanta ATIS-KIOSK Project

The Atlanta KIOSK ITS FOT was the evaluation of an ATIS system in Georgia. The purpose of the project was to provide the traveling public with a diverse base of pertinent information available through an easy-to-use interface located at many transportation interchanges. The kiosk system continues to operate after the completion of the test and is available statewide through a system of over 130 kiosks. Available information includes route-maps, local attractions, real-time traffic and incident information, airport information, Metropolitan Atlanta Rapid Transit Authority (MARTA) information, and special events and Olympic schedules (during the 1996 Summer Olympic Games).

The test evaluation was halted mid-way due to lack of funds. A modified evaluation strategy was developed and implemented for User Acceptance only. The results showed that travelers who used the kiosks found them user-friendly and useful. The percentage of usage, however, remain low, varying from 8.6% of possible users at one tourist center to 0.1% at a busy MARTA station. The test partners were Clark Atlanta University, Concord Associates, FHWA, Georgia DOT, Georgia Net, Georgia Tech Research Institute, and JHK (Transcore).

Atlanta Driver Advisory Service (ADAS)

The ADAS ITS FOT assessed a comprehensive ATIS system. In the Atlanta metropolitan area, ADAS provided information to drivers of 170 vehicles equipped with receiving units. The main objective of this operational test was to evaluate the performance of the wide area driver advisory (WADA) system, the two-way messaging system, and the local area driver advisory (LADA) system. The test data collection occurred from October to December of 1996.

The WADA demonstrated its capability to collect and transmit congestion and incident information from the ATMS to the vehicles. Reception of messages, however, was only around 58% instead of the desired 99% and coverage was only 48% instead of the desired 95%. ADAS was able to demonstrate the capability of exchanging messages with test vehicles. The rate of success was only 70% rather than the desired 95%. The LADA service successfully demonstrated its capability to transmit and receive traveler information. The in-vehicle system was able to use the Global Positioning System (GPS) to properly tune to the receiver to the correct frequency and receive the appropriate information. In some cases, however, the in-vehicle signs and traveler service maps did not appear with sufficient lead time before an exit.

The test partners were Clark Atlanta University, Concord Associates, Federal Express, Georgia DOT, Georgia Tech Research Institute, Oak Ridge National Laboratory, Scientific Atlanta, and TRW. A full report on this FOT can be found in Garnto (1997).

Boston SmarTraveler

The Boston SmarTraveler ATIS FOT offered free, real-time, route-specific traffic and public transportation via telephone to users in the Boston metropolitan area. The test proposed to assess the quantity and quality of information provided by the system, evaluate its public acceptance, and determine its impact on managing traffic congestion. This project began in October 1992 and its service was extended to the end of 1994. The test partners were FHWA, Massachusetts Highway Department, and Smart Route Systems.

The following findings were reported by Multisystems, Inc. (1993):

(1) Awareness of SmarTraveler among the target population was limited.

(2) 97% of respondents indicated that they would use the service again.

(3) Daily calls increased at a steady rate but did not reach a sufficiently high level during the test period to have meaningful impacts on congestion.

Colorado MAYDAY

The Colorado MAYDAY FOT implements and evaluates an automated mayday system. The system allows users to request help and provides authorities with specific information about the location of the motor vehicle and the type of roadside assistance required. The test area includes the City of Denver and several counties in the northeast quadrant of Colorado, covering about 12,000 square miles and including both rural and urban roadways. The project started in 1995 and the final report is expected in 1998.

The Colorado MAYDAY system consists of an in-vehicle device, a response center, and a dispatch center. The in-vehicle device is called TIDGET. The TIDGET provides GPS data and

contains the communications system control equipment. Depending on the distress situation, the user activates the appropriate button on the box and the TIDGET sends data on the vehicle location and the requested service to the response center. The Colorado MAYDAY system uses an analog cellular two-way wireless communication system. The response center calculates the vehicle position using the raw GPS data sent by the TIDGET and sends the information to a dispatch center.

In areas with favorable cellular coverage, the system was found capable to calculate a vehicle position that is sufficiently accurate (averaging within 82 meters). In areas of marginal to non-existent cellular coverage, the analog cellular system was unreliable in transmitting data. Nevertheless, when the system could not determine a position, it would default to voice-only mode. The test partners were AT&T Wireless, Inc., Colorado DOT, ESRI, FHWA, NAVSYS Corporation, and The ENTERPRISE Group. Reports of this FOT can be found in Castle Rock Consultants (1995; 1997).

Driver Information Radio using Experimental Communication Techniques (DIRECT)

DIRECT ITS FOT deployed and evaluated five alternative low-cost methods of communicating travel information to motorists in the Detroit metropolitan area, namely, Radio Data Broadcast System (RDBS), FM subcarrier, Automatic Highway Advisory Radio (AHAR), Low-Power Highway Advisory Radio (LPHAR), and cellular phone. The system sends travel information to a group of test vehicles and then tracks the vehicles during their commute. The field evaluation phase began in April 1996 and concluded in December 1997.

Interim results indicated that:

(1) Drivers wanted specific types of information, such as unexpected delays, location of incidents, length of delay, advice on whether to divert, and alternate routes.

(2) The technologies involving extensive field components (LPHAR, AHAR, EDBS) were difficult to maintain and, therefore, less reliable.

(3) Drivers did not feel that the DIRECT system they used was a significant improvement over commercial radio traffic information, but was an improvement over television traffic information and changeable message signs.

The test partners were AAA of Michigan, Capstone/Ameritech, Delco, Ericsson/GE, ERIM, FHWA, Ford Motor Company, General Motors, Metro Networks, Michigan Emergency Patrol, Michigan State Police, and WDTR FM Radio. An interim report on this FOT can be found in University of Michigan ITS Research Lab (1997).

During Incidents Vehicles Exit to Reduce Time (DIVERT)

The DIVERT FOT was previously named the St. Paul Incident Management. A partnership among FHWA, Minnesota DOT, City of St. Paul, and Safetran Traffic Systems, inc., it demonstrated the feasibility and effectiveness of diverting freeway traffic onto pre-planned diversion routes along the surface streets during freeway incidents. The test became operational in December 1996 and the evaluation is expected to complete in 1998.

If a major incident occurred on the test freeway section, traffic managers will divert traffic incidents to arterial bypass routes using surveillance and guidance equipment (such as VMS,

cellular phone-based notification system, and static trailblazer signs) and coordinated signal timing plans.

Faster and Safer Travel Through Traffic Routing and Advanced Control (FAST-TRAC)

FAST-TRAC demonstrated an improvement in mobility and safety on the increasingly congested arterial roads and freeways of Oakland County, Michigan. This project intended to combine ATMS component – the Australian SCATS (Sydney Coordinated Adaptive Traffic System), with ATIS component – the roadside beacon-based Siemens Ali-Scout system. This deployment commenced in 1991. The Ali-Scout component was eliminated in 1998 but the SCATS component will continue until 2000.

Initial findings of this test indicated that:

(1) Installation of the system resulted in increases in average speeds of up to 19% on major arterial roads during peak periods and in the peak direction of travel.

(2) At several intersections, average delay decreased on major road approaches but increased on minor approaches.

(3) A significant benefit of installing the system has been the flexibility it provided traffic managers to respond to changes in traffic flow, local policies, special events, and other consideations.

The test partners were AWA Traffic Systems - America, Chrysler Corporation, City of Troy, County of Oakland, FHWA, Ford Motor Company, General Motors, Michigan DOT, Michigan State University – Detroit, Nissan Motor Company, Road Commission for Oakland County, Siemens Automotive, and University of Michigan – Ann Arbor. An interim report on this FOT can be found in Public Sector Consultants (1995).

GENESIS

The Genesis FOT demonstrated the use of alphanumeric personal communications devices (pagers) and personal digital assistants (PDAs) to rpovide traffic information in the Twin Cities Metropolitan area of Minnesota. The operational testing phase began in mid 1995 and finished in January 1996. The test partners were FHWA, MinnComm, and Minnesota DOT.

The final project report prepared by Booz • Allen & Hamilton (1997) indicated that the use of PDAs were extremely limited due to technical difficulties, and the preponderance of available data came from pager users. Genesis was found to be quite effective in diverting incident traffic compared to other communication means (radio, television, etc). The overall user ratings of the usefulness of the system were positive.

Integrated Corridor Traffic Management (ICTM)

The ICTM FOT uses advanced adaptive control technology to improve traffic efficiency along an eight-mile segment of the I-494 corridor south of the Minneapolis-St. Paul metropolitan area. The test is currently operational and evaluation data collection is underway. Originally scheduled for completion in December 1998, the test has been extended by one year to provide a longer evaluation period. The main objectives of this test are:

(1) Implement an adaptive traffic control strategy that rapidly responds to anticipated and unanticipated fluctuations in traffic flow.

(2) Integrate available advanced technologies to collect and disseminate corridor information.

(3) Provide comprehensive motorist information services.

The ICTM partnership includes Cities of Bloomington, Edina and Richfield, Hennepin County, FHWA, Minnesota DOT, and TransCore.

Seattle Wide-area Information For Travelers (SWIFT)

The SWIFT FOT evaluated the performance of a large-scale, urban ATIS deployment in Seattle, Washington. The SWIFT project tested the ability of a high speed FM subcarrier to deliver traveler information to users via a paging watch, a laptop computer, and an in-vehicle navigation device. Testing of this system took place from August 1996 to September 1997. Washington DOT's Freeway Management System would send information to laptop computers, which in turn, would plot incidents on a mapped data base. The Message Watch would alert the commuter to problems for routes and times as specified in the user's individual travel profile. The in-vehicle navigation device also included a yellow page directory with GPS to show location and relative direction to selected destination. The test partners were Delco Electronics, ETAK, IBM, Metro Traffic, Seiko Communications Systems, University of Washington, SAIC.

TransCal Interregional Traveler Information System

The TransCal FOT evaluates an Interregional Traveler Information System (IRTIS). It provides coverage for the Interstate 80 and US 50 corridor between San Francisco and Tahoe/Reno-Sparks area. The IRTIS proposed to provide an integrated service that includes road, traffic, transit, weather, and value-added traveler services from various sources, via telephone, PDAs, and in-vehicle navigation devices (IVDs) as well as traditional broadcast media. The testing of the PDAs and IVDs will finish by 1998. The test partners are California DOT, CHP, FHWA, Metropolitan Transportation Commission, Nevada DOT, NHP, RTCWC, Sacramento Council of Government, Sierra Counties Consortium, Tahoe Trans District, and TRW.

Travel Technology (TravTek)

The TravTek ITS FOT contained a series of field tests, experiments, and analytical studies focused on ATIS and ATMS concepts, conducted in Orlando from November 1991 to June 1994. TravTek consisted of three main components:

(1) The TravTek In-Vehicle System was installed in 100 AVIS rental vehicles.

(2) The information was collected and processed at the Orlando Traffic Management Center.

(3) Customer information and services were provided by the TravTek Information and Services Center.

The results indicated that the TravTek system was reliable and the probe vehicle concept worked well. However, a need for better incident reporting was identified. The system was also found to save trip-planning time and reduce travel time. There were marked differences between visiting users and local users in terms of usage frequency, display configuration selection, willingness to pay for this service/system. The TravTek partnership consisted of American

Automobile Association, City of Orlando, General Motors, and the FHWA. The evaluation report can be found in Turner Fairbanks Highway Research Center (1996).

TravInfo

The TravInfo FOT evaluates a regional ATIS system in the San Francisco Bay Area, providing up-to-the-minute traffic information and current transit and ride-share information through a regional no-area-code telephone number. It aims to:

(1) Collect, integrate, and broadly disseminate timely and accurate traveler information throughout the San Francisco Bay Area.

(2) Stimulate and support the deployment of a wide array of ATIS products and services leading to the creation of a competitive and viable market.

(3) Test the value and effectiveness of a public/private partnership to collect and disseminate traveler information.

The test partners are California DOT, CHP, FHWA, Metropolitan Transportation Commission, and TRW. The test began operations in October 1996 and will continue until December 1998.

Trilogy Advanced Traveler Information System Operational Test

The Trilogy test broadcasts traffic information about the Twin Cities expressways to in-vehicle devices. The test provides in-vehicle devices that deliver information in map-graphic and icon format (AB Volvo Dynaguide) to approximately 150 drivers from 5 companies, and approximately 30 private users (commuters). HNTB's interim evaluation report (1997) indicated that the tested device provided reliable and accurate traffic information to users. Most users considered the information provided by the system to be of better quality than previously available sources. They perceived stress reduction, improved safety and added comfort. They have also identified a few aspects of the system that should be improved, including device coverage area limitations and restricted text message access. Though users were able to define reasonable price ranges for Trilogy product and services, they could not readily justify a personal purchase of the system. The test partners are AB Volvo, Differential Correction Systems, FHWA, and Minnesota DOT.

SUMMARY

This chapter has presented a review of research related to the study of the complex commuter behavioral dynamics in response to real-time traffic information, including a survey of more conventional methods of measurement in the area of transportation demand as well as more advanced and innovative approaches to study travel behavior. Emphasis has been given to the interactive computer driver simulators developed for the investigation of commuter behavior in response to ATIS systems. A general discussion of the behavioral aspects of ATIS system implementation and deployment has also been provided, addressing four choice dimensions of ATIS system users, namely, acquisition of the equipment, consultation of the information system, compliance with its instructions, and trip decisions and actions. A comprehensive synthesis of all sixteen ATIS-related Field Operational Tests in the United States are furnished in this chapter as

well. Included in it are each project's description, testing period, partnership members, and lessons learned.

The next chapter discusses the research methodology used to study the dynamics of commuter behavior under real-time information, including the dynamic travel simulator as well as the design of the interactive laboratory experiments.

CHAPTER 3: RESEARCH METHODOLOGY

INTRODUCTION

The methodology for user behavior research of this nature consists of two parts:

(1) observation of actual driver behavior through interactive, laboratory-like experiments, and

(2) analysis of data collected and modeling of driver behavior.

As discussed previously, the appropriate observational data at the level of richness is clearly quite difficult to obtain in a real-world context. It would require the participation of a sizable fraction of the users affecting a system's performance, large-scale monitoring of the facility, and a high degree of control by the experimenter, which would be impractical and prohibitively expensive. Thus, in this research study, a dynamic interactive travel simulator with multiple-user capability has been developed and used for behavioral observation of actual commuters in response to different scenarios of interest in a carefully-designed simulated traffic system. This allows the researcher to observe the participants' underlying decision-making processes on trip-making choices under the variability of the system performance in a controlled laboratory-like settings. Behavioral experiments of this kind provide a critical observational basis for the study of complex large-scale dynamic systems, bridging between speculative or highly idealized theoretical development on one hand, and full-scale field studies, in which the desired level of experimental control may not be practical, on the other.

Simulators have traditionally been used for training purposes (Jones, Hennessy, and Deutsch, 1985). For instance, a flight simulator is used interactively to train pilots to familiarize with the tasks, acquire skills and practice segments of, or complete, missions. Simulators as such emulate all or part of the actual system and facilitate individual or group training. Interactive simulators have also been used to conduct decision science research, such as de Neufville and Delquie's work in preference assessment (1988), as well as applied marketing research, as illustrated by Hauser, Urban and Weinberg's work on the value of information and its effect on consumer choice (1992). In transportation research arena, driving simulators were used in experiments to study drivers' braking behavior and emergency maneuvers in sudden and unexpected situations (Barrett, Kobayashi, and Fox, 1968; Malarterre and Lechner, 1990). Other driving simulators were used to study subjective trip time estimations (Leiser and Stern, 1988).

Several travel simulators have been developed to study driver behavior in the presence of emulated ATIS systems as described previously in Chapter 2. All of these simulators, however, are either deterministic, with all traffic conditions and consequences of driver actions predetermined and no consideration of network-wide traffic characteristics, or stochastic, with link

travel times derived from some probabilistic distributions. These simulators are limited to handle one subject at a time, ignoring interactions among drivers in the same traffic system. Most simulators provide different preset levels of information quality to the experimental subject, in an arranged sequence. In addition, the effect of the drivers' responses to the information on the traffic system is not considered. Some of these simulators assume the information supplied to be perfect and static, which is not representative of actual real-time ATIS environments.

A new simulator is presented in this chapter. This simulator offers the capability for real-time interaction with and among multiple driver participants in a traffic network under ATIS. It allows several drivers to "drive" through the network, interacting with other drivers and contributing to system evolution. Moreover, it considers both system performance as influenced by driver response to real-time traffic information and driver behavior as influenced by real-time traffic information based on system performance. This simulator is dynamic in the sense that it actually "simulates" traffic. Its "engine" is a traffic flow simulator and ATIS information generator (DYNASMART), that displays information consistent with the processes actually taking place in the (simulated) traffic system under the particular information supply strategy of interest. The decisions made by the driver participants are feed directly to the simulator, and as such influence the traffic system itself and the subsequent stream of information stimuli provided to the participants.

This dynamic interactive simulator has been designed to study not only commuter decisions under real-time ATIS information for a particular commute on a given day, but also the day-to-day evolution of individuals' decisions under such information strategies as they become more familiar with traffic system and the real-time information. This longer-term dimension is missing from most available studies of the effectiveness of ATIS. This report considers system evolution and possible equilibration by including the participants and the simulator in a loop whereby tripmakers may learn and adjust their decisions from one iteration day to the next.

A series of controlled "laboratory-like" interactive experiments involving real commuters in a simulated traffic system has been conducted in this research study. These experiments involved commuters supplying departure time and route decisions in response to a spectrum of different real-time ATIS strategies of varying degree of information quality in a simulated traffic system using this simulator. By actually simulating traffic conditions in response to the supplied commuter decisions, the simulator provided stimuli to the participants that were always consistent with physically realistic traffic behavior, and with their previous actions.

It should be emphasized here that the development of the simulator as well as the design of these behavioral experiments have embodied a school of work of over fifteen years, accomplished by Mahmassani, Herman, Chang, Tong, Jayakrishnan, Stephan, Caplice, Hatcher,

Joseph, Jou and Chen at the University of Texas at Austin. The theoretical validity and physical consistency of the simulator and the experiments are firmly supported by this school of work, including Mahmassani, Herman, Chang, Tong, and Stephan's work on interactive experiments for the study of day-to-day dynamics of tripmaker behavior, Mahmassani, Walton, Caplice, Hatcher, Joseph, and Jou's work on survey diaries to obtain detailed information about the actual behavior of commuters, as well as Mahmassani, Jayakrishnan, and Chen's work on simulation assessment of the ATIS systems in reducing traffic congestion and of the interactions among key factors, such as nature and amount of information, market penetration, congestion severity, and information reliability.

This chapter is organized as follows. The first section provides a background discussion of the previous research experience at the University of Texas at Austin. The following section presents the details of the dynamic interactive travel simulator. The third section describes the system architecture of the dynamic interactive simulator used in the experiment. Some of the unique features of this simulator are presented, followed by a description of the interface between the "driver" and system, as well as the associated experimental response tasks performed by the participating commuter subjects. The traffic simulation and path assignment model (DYNASMART), which forms the simulation engine to dynamically represent the evolution of traffic conditions, is discussed, including the path selection and switching rule governing the decisions of the simulated drivers (background traffic in the experiment). The following section provides a description of the design and setup of the laboratory experiment. The particular commuting context adopted in this particular experiment to investigate the commuters' behavior under real-time information is presented. The apparatus set up to collect the commuters' responses is also described. Experimental design and experimental procedure are depicted. The process followed to recruit subjects for this experiment is provided and finally a summary of this chapter is given.

PREVIOUS RESEARCH EXPERIENCE

This section discusses the various research work accomplished at the University of Texas at Austin in the area of commuter behavior dynamics since the early eighties, up to and until the conceptualization of this research study. The body of knowledge gained from these earlier work is most relevant in ensuring the necessary theoretical validity as well as external and internal consistencies, as required by the kind of interactive experiments conducted in this research whereby the variability of tripmaker decisions in response to real-time information are observed simultaneously with the service levels experienced in congested traffic systems.

Mahmassani and Chang (1986) first introduced a framework for the day-to-day adjustments of departure time decisions in response to experienced congestion, incorporating a traffic simulation model to investigate the dynamics of a morning commuting system under alternative rules for departure time adjustment and learning from day to day. This exploratory work later evolved in three directions: (1) a series of interactive laboratory-like experiments were conducted with actual commuters, and the observational data were used to refine and calibrate decision process models; (2) field surveys were conducted in the form of trip diaries to collect detailed information on actual commuting trip decisions, and the recorded data were used to confirm and validate the experimental results; and (3) the original modeling framework was expanded to perform simulations of the day-to-day, within-day, and more recently, real-time variability of the commuting system under alternative scenarios to evaluate the effectiveness of various ATIS/ATMS strategies. A review of this body of work in the area of commuter behavior dynamics can be found in Mahmassani (1996).

Laboratory Experiments

Three interactive, laboratory-like experiments were conducted, aiming at investigating the day-to-day dynamics of commuter behavior in congested traffic systems. This experimental approach introduced by Mahmassani, Chang and Herman (1986) involved actual commuters interacting through a simulation model of a typical traffic commuting system under different information strategies. The first two experiments involved a single highway facility, restricting commuters to only departure time choice, whereas the third experiment consisted of two parallel roadway facilities, thereby allowing commuters both departure time and path choices.

The participants received one of two different information strategies (limited information versus full information) for the morning commute. Under the limited information strategy, i.e., the commuter's own experience in the traffic system as the only source of information available, the participants make their travel choices based on his/her actual travel time on the preceding day (corresponding to the specific departure time and/or route selected on that day). Under the full information supply strategy, information was available from exogenous sources and participants were provided with all the arrival times from the preceding day, including the full spectrum of possible departure time alternatives. One hundred staff members and actual commuters at the University of Texas at Austin each participated in the first two experiments, whereas the third experiment had two hundred participants.

The results suggested that the effects of exogenous information on user behavior and system performance appeared to depend critically on the fraction of the population with access to such information, and, more generally, on the distribution of the type and extent of information across the population. Furthermore, it was concluded that the boundedly rational notion of an

indifference band was found to provide a plausible explanation of the commuter behavior under information availability as observed in these experiments. The effects of information availability on the behavior and system performance investigated in this series of studies are summarized in Mahmassani and Herman (1990).

Field Study

A survey diary approach was developed at the University of Texas for the purpose of collecting detailed information of actual behavior of commuters under relatively uncontrolled conditions (Mahmassani, Caplice and Walton, 1989). This survey approach has been conducted in the state of Texas, first Austin, and then, in a larger scale, Dallas. Commuters were asked to provide detailed record about times of departure and arrival, detailed link composition of the path followed, intermediate stops and their characteristics (purpose, timing, duration), and if they received pre-trip traffic information, for both morning and evening commutes over a two-week period.

The analysis revealed a remarkable similarity between the two cities in the general patterns observed as well as the magnitude of several characteristics. The differences observed, nevertheless, appeared to be primarily induced by the relatively larger size of the Dallas area, its subsequently greater number of path opportunities in the network, the associated longer commutes, and greater and longer periods of congested operation. A model of commuters' joint departure time and route indifference bands (following the boundedly rational framework) incorporating trip chaining was developed based on the data collected in both the Austin and Dallas. The model results confirmed the role of the preferred arrival time as anchor for trip scheduling decisions, and as an indicator of inherent individual preference and attitude towards risk. They further validated the role of schedule delay as a critical determinant of commuter decision dynamics and response to congestion (Mahmassani and Jou, 1996).

Simulation Studies

The modeling framework used to study the day-to-day dynamics of commuter behavior in congested traffic systems was expanded and further developed to analyze the effect of in-vehicle real-time information strategies on the performance of a congested traffic commuting corridor of three parallel highway facilities (Mahmassani and Jayakrishnan, 1991; Chen and Mahmassani, 1991; Mahmassani and Chen, 1991; Mahmassani and Chen, 1993). Several simulation experiments were performed under this expanded modeling framework, investigating the effect on overall system performance as well as the incidents of benefits (costs) across user information groups of four experimental factors: (1) behavioral rules, governing users' responses to real-time information; (2) sources of information, consisting of point-of-departure or in-vehicle (or both); (3) prevailing "initial conditions" in the system; and (4) market penetration (i.e., the fraction of users

with access to real-time information in the network). The issue of information reliability was also explored, employing a specially developed traffic probing mechanism to collect travel information and provide comparative measures of reliability.

The results confirmed the a priori expectations that the existence of benefits as well as the effectiveness of real-time information was highly dependent on the initial conditions prevailing in the system as well as the behavioral rules governing path selections. Switching according to a boundedly rational model incorporating a threshold (indifference band) of improvement in trip time was more likely to lead to meaningful system-wide benefits. Moreover, the reliability of real-time information were inclined to decrease with increasing market penetration of the technology, as the larger fraction of users who responded to the information generated rapid changes in traffic conditions and growing discrepancies between actual and supplied trip times. Market penetration of 25% was found to be the desirable limit beyond which travel time improvements might be hard to realize without some form of coordination (by a central controller) in the provision of information in an ATIS.

THE DYNAMIC INTERACTIVE SIMULATOR

System Architecture

The simulator developed to perform the interactive experiments is an application of the client/server modeling concept used extensively in X Window System applications (Johnson and Reichard, 1989), as shown in Figure 3.1. The simulation-assignment model (as an X client) used is an extension of the corridor model developed by Mahmassani and Jayakrishnan (1991) and modified by Mahmassani and Chen (1991) to include pre-trip path selection in addition to en-route switching decisions. Another program controls the layout of windows displayed on the screens of a set of Macintosh, IBM PC compatible, X terminal, DEC Alpha Workstations and Intergraph computers interconnected through a local area network. This program is linked to the simulation-assignment model using a number of C library interface routines. The participants receive the real-time information via the computer monitor and use the keyboard or mouse to input their responses during the experiment. All user responses are input to the simulation-assignment model and thus directly influence prevailing traffic conditions to create a dynamic traffic environment.

Unique Features

This interactive simulator possesses several unique features for investigating tripmaker behavior under ATIS. Firstly, it offers multiple user capabilities, whereby a number of users can participate as decision makers responding to supplied information simultaneously, with each receiving information that is specific to their situation or position in the traffic network, yet insuring

that the information is consistent with (the simulated) traffic reality for all users. Therefore, data can be collected on several subjects (as many as one hundred subjects at the same time) simultaneously, all of whom are interacting in real-time with the prevailing traffic situation. Secondly, the simulator is dynamic, as all participants' responses are input as they occur to the simulation-assignment model and thus directly influence prevailing traffic conditions. There are no predetermined consequences for the subjects' responses, other than those that result from the nonlinear interactions taking place in the traffic system. Thirdly, this simulator can be run in real time. It is calibrated in such a way that every simulation time step conforms to the speed of the host computer's clock. Naturally, other desired simulation speeds can also be achieved. Lastly, it supports experiments intended to be collective but not collaborative in design. Information supplied to each subject is tailored to reveal network traffic conditions that pertain to the subject him/herself only. The subject cannot obtain direct information on other subjects in the system through the simulator, although talking among participants, such as comparing commuting experiences, is not prohibited. In summary, our interactive simulator provides participating commuters a dynamic commuting environment in which they can interact with one another and with the simulated system in a real time setting.

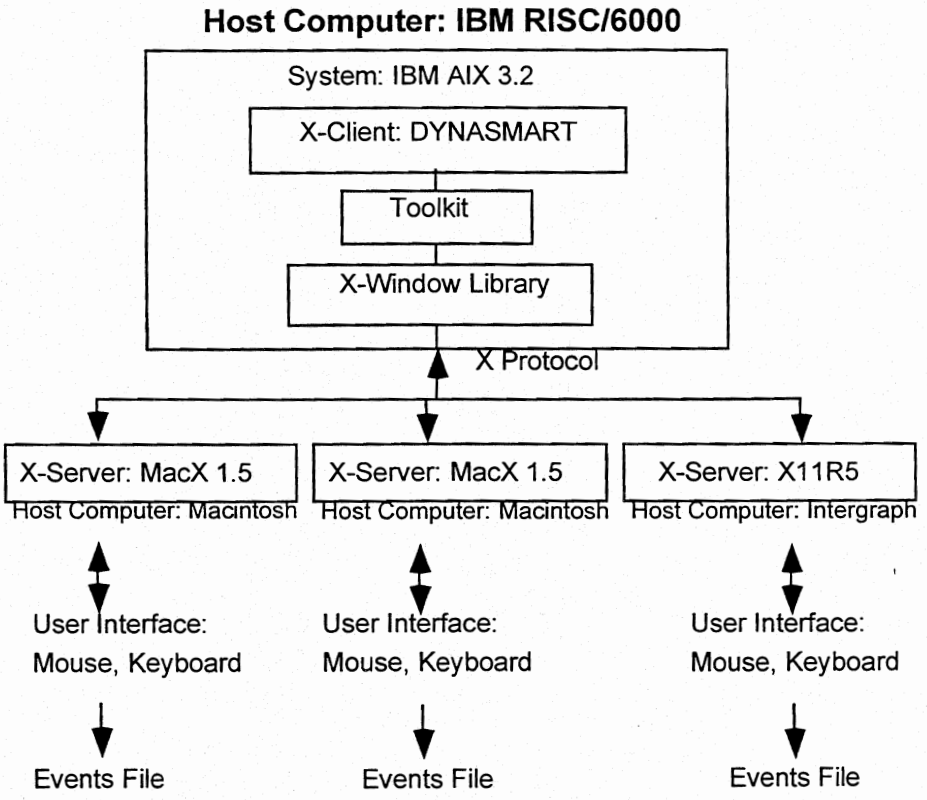


Figure 3.1: The Client/Sever Model

Driver/Machine Interface

All the human/machine interfacing with a given participant takes place via the computer (Macintosh personal computer in this case) assigned to him/her. Information to participants is shown on the monitor screen and each participant uses the mouse to move the cursor to the space provided on the screen or the keyboard to click or type in his/her response. A sample of the layout of the information displayed on the monitor screen is shown in Figure 3.2. Each participant is provided with a view of the basic network configuration and his/her relative vehicle position in the network at all times. Each participant's vehicle is moved according to his/her decisions in real time. Different situational messages are shown to him/her in the space provided on the screen as determined by the traffic system's evolution, as shown in Figure 3.3. Participants are alerted by a "beep", produced by the built-in audio device in computers every time a message appears on screen. Because the simulator utilizes the X window system, it is very easy to add or delete messages (information) when needed. Human factors engineering considerations were taken into account in the development process to follow principles of design such as good visibility, natural mapping, and good feedback (Norman, 1988; Rubinstein and Hersh, 1984). Moreover, the amount of information displayed to subjects at any given time has been limited to prevent overloading the subject's short-term memory (Kahneman, 1973).

Traffic Simulation and Path Assignment Model (DYNASMART)

The simulation-assignment model is based on the corridor network version of the DYNASMART model developed at the University of Texas at Austin. The model is comprised of three main components: the traffic performance simulator, the network path processing component, and the user decision-making component, as shown in Figure 3.4.

The traffic performance simulator is a fixed time-step mesoscopic traffic simulator. Vehicles on a link are moved individually at prevailing local speeds consistent with macroscopic speed-density relations (modified Greenshield's model). Inter-link transfers are subject to capacity constraints. For the given network representation and link characteristics, the simulator uses a time-dependent input function to determine the associated vehicular movements, thereby yielding the resulting link trip times, including estimated delays associated with queuing at nodes. These form the input to the path processing component, which calculates the pertinent path trip times, which are in turn supplied to the participating commuters and the user decision component. The latter is intended to predict the responses of the simulated commuters in the system to the available information according to a set of behavior rules, as described below. This capability allows us to control the fraction of users in the system that are equipped with ATIS devices. The simulator considers a wide range of information strategies, from supplying prevailing trip times on the network links with no attempt by some central controller or coordinating entity to predict future

travel times, to providing individual-level route guidance based on reliable travel time predictions such as the employment of traffic probes. Another function of the path processing component is to translate the user path selection and switching decisions into time-varying link flow patterns on the network's links. Further detail on the simulation-assignment methodology can be found in the papers by Mahmassani and Jayakrishnan (1991) and Jayakrishnan, Mahmassani and Hu (1994).

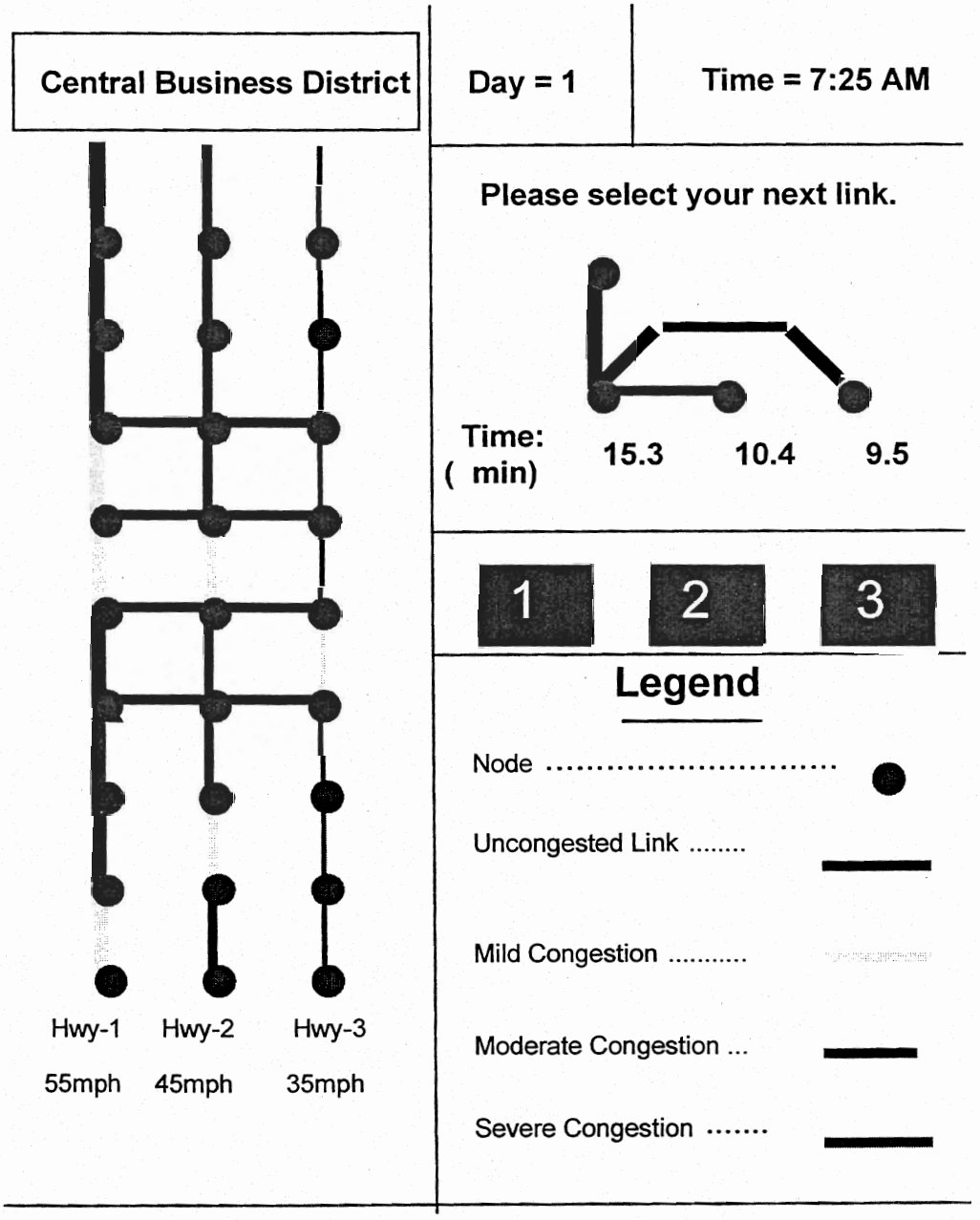


Figure 3.2: Layout of information display in dynamic simulator

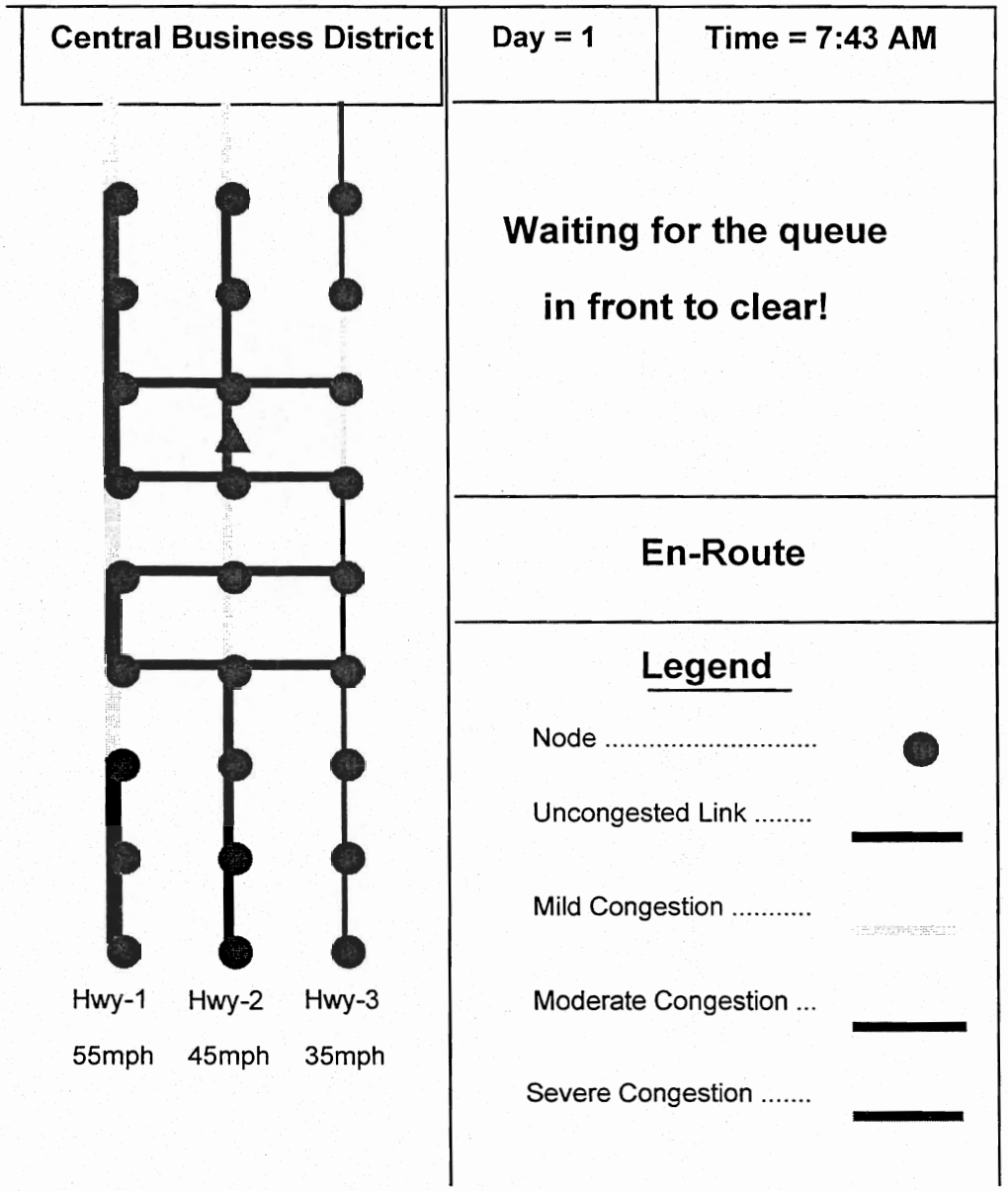


Figure 3.3: Situation Message Display

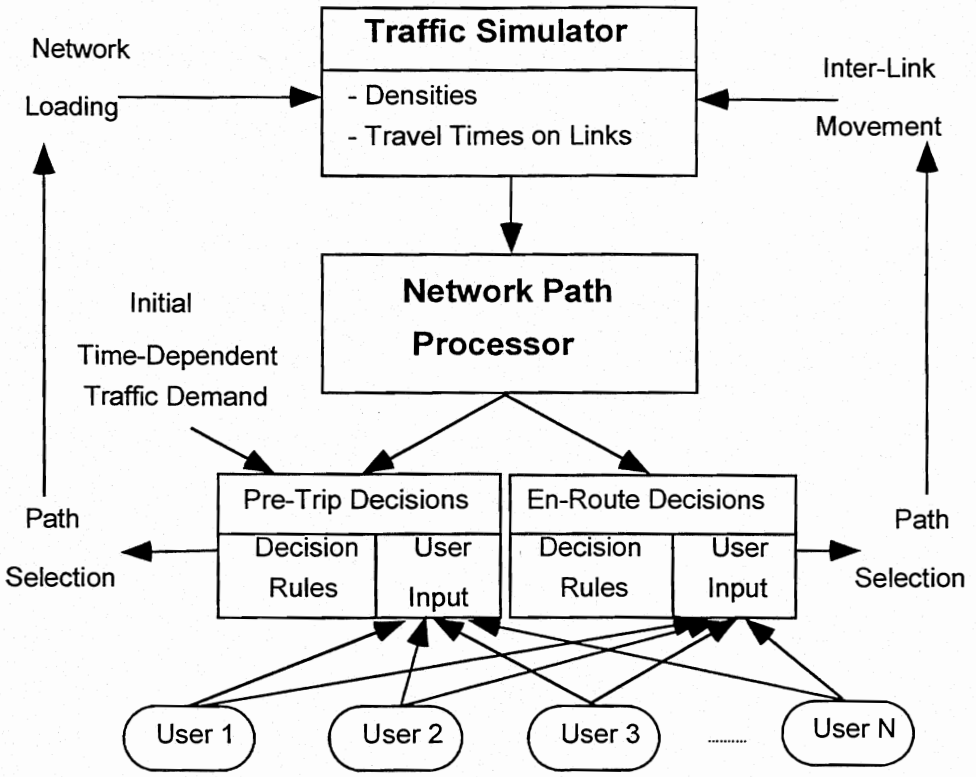


Figure 3.4: The Simulation-Assignment Model

During this experiment, commuters' route decisions may be made by actual participants, as well as by simulated drivers, reflecting the desired fraction of equipped users in the simulated system. The boundedly rational rule has been adopted in the user decision component for both pre-trip route selection and en-route path switching. Following Mahmassani and Jayakrishnan (1991), this rule is operationalized as follows:

$$\phi_{ijt} = -1, \quad \text{if } TTC_{ijt} - TTB_{ijt} \leq \max [\eta_{ijt} TTC_{ijt}, \pi_{ijt}]$$

$$\phi_{ijt} = 1, \quad \text{otherwise} \qquad (3.1)$$

where

ϕ_{ijt}: a binary indicator, which equals 1 if user I switches from the current path to the shortest path at node j on day t; -1 otherwise

TTC_{ijt}: the trip tome on the current path from decision node j to user i's destination on day t.

TTB_{ijt}: the trip time following the shortest path from decision node j to user i's destination on day t.

η_{ijt}: the relative indifference band, as a fraction of the TTC (trip time along the current path) from decision node j to the destination for user i to switch from the current path on day t.

π_{ijt}: the minimum trip time savings, from decision node j to destination, necessary for user i to switch from the current path on day t.

It is important to note that in this experiment, there are two sources of driver decisions in the system. First, the actual participants themselves provide decisions that are directly incorporated in the simulation, immediately affecting the paths of the corresponding simulated vehicles. The second source of decisions are the behavioral rules in the user decisions component for those simulated drivers that are "equipped" to receive real-time information in the simulated system. Of course, a particular equipped vehicle is governed by only one of the above two sources of decisions.

Each simulated driver with ATIS devices is assigned a randomly generated indifference band, η_{ijt}, drawn from a triangular distribution with mean $\overline{\eta}$ and range $\overline{\eta}/2$. These assigned bands remain fixed over the duration of any given trip. Since it was found previously that a mean indifference band of 0.2 appears to provide reasonable overall behavior as well as the largest systemwide improvement in travel time (Mahmassani and Jayakrishnan, 1991; Mahmassani and Chen, 1991), the level of $\overline{\eta}$ is set at 0.2. Furthermore, while η_{ijt} is allowed to vary across users, a minimum absolute improvement threshold, π_{ijt}, set at 1 minute, is taken to be identical across all simulated users with information.

THE LABORATORY EXPERIMENT

The Commuting Context

In this experiment, the participants interacted with each other within a simulated traffic corridor that consisted of three parallel facilities, highways 1, 2, and 3 with speed limit 89 km/hr (55 mph), 72 km/hr (45 mph), and 56 km/hr (35 mph), respectively. The cross-over links had a free mean speed of 72 km/hr (45 mph). Each of the three highways was nine miles long, and each was discretized into nine one-mile segments, with cross-over links at the end of the third, fourth, fifth, and sixth miles to allow travelers to switch from one highway to any of the other two based on the real-time information provided by the system. The tripmakers could determine their departure time and route selection before starting the trip and their path en-route as they approach the nodes of these cross-over links. The layout of the test network is shown in Figure 3.5.

This experiment involved pre-trip departure time and route selection as well as en-route path choices. Simulated drivers enter the corridor through ramps feeding into each of the first six one-mile segments on each facility and commute to a single common destination downstream (such as the Central Business District or a major industrial park). The equipped commuter received information on the prevailing trip times from user's present location (either at the origin or en-route) to his/her destination along the three alternative paths.

Apparatus Setup

The test apparatus consists of an IBM RISC System/6000 to run the simulation-assignment model (corridor version of DYNASMART) written in FORTRAN. An additional program is written in C language with X library functions (X Window System version 11, release 5) to control the layout of windows displayed on the screens of a set of Macintosh computers (used by subjects, one computer per subject) on which X window software (MacX 1.5) is being run. This program is linked to the simulation-assignment model using a number of C library interface routines available under IBM AIX version 3.2, an implementation of the AT&T System V-based version of the UNIX operating system. X Window System protocol is a low-level graphics description language used by the X clients and servers to exchange information.

To simplify the experimental procedure, commuters were asked to participate in small groups of five to ten participants interacting with one another during the commute. Ten Macintosh computers were used as front-end host computers, connected via the Ethernet network in the Civil Engineering Learning Resource Center at the University of Texas at Austin.

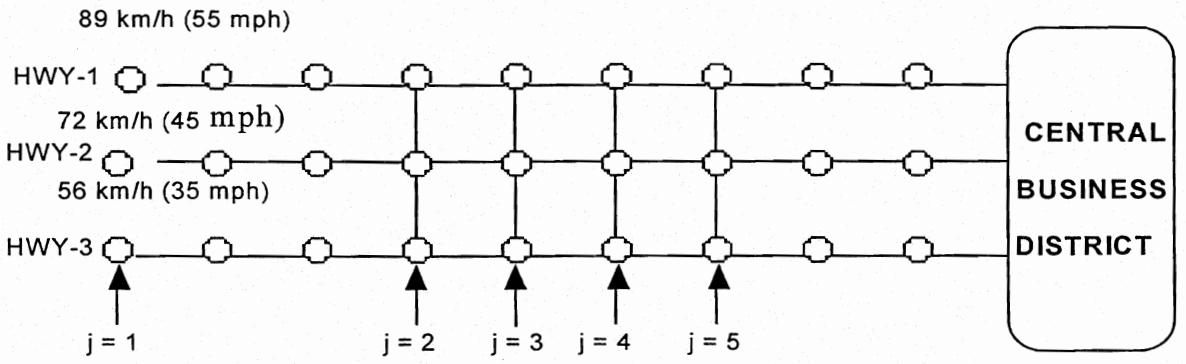


Figure 3.5: Commuting corridor with three parallel facilities

Experimental Design

In the experiment, a commuter faces three principal decision situations when supplied with real-time traffic information: (1) pre-trip planning and adjustment, (2) en-route assessment and diversion, and (3) post-trip evaluation (Figure 3.6). At the post-trip evaluation stage, a commuter examines the trip he/she has just completed against the actual post-trip data for that day, and implicitly decides his/her intended departure time and route for the next day's commuting trip. When he/she "gets up in the morning", he/she can either follow the departure time and route decided from the previous day or change to other times and/or routes based on the pre-trip information. Once the commuter begins the trip, the only choice dimension that remains available to the tripmakers is to switch routes in response to the congestion reported by the en-route ATIS.

A total of 10800 simulated commuters, split equally among the first six (residential) sectors, share the use of facilities in the corridor during the morning commute. Commuters in each sector depart uniformly over a 20-minute period; the loading periods for each sector are staggered with a time lag of five minutes between adjacent sectors, with Sector 1 starting first. During the experiment, 60 vehicles enter Highway 1, 20 vehicles enter Highway 2, and 10 vehicles enter Highway 3, all per minute per sector. Note that this assignment constitutes intended paths for the commuters. If origin-based real-time information is available, the actual initial path selected by commuters with access to such information is followed by the boundedly rational rule described. The simulated commuters without equipped traffic advisory units do not switch routes and follow the pre-specified route along their commute. As the simulated vehicles are generated in each simulation time step, individual vehicles are assigned their information availability status randomly and independently according to the fraction of market penetration specified previously.

As part of this experimental design, twenty-five percent of the simulated commuters (background traffic) received real-time traffic information from an in-vehicle traffic advisory unit. The equipped commuter receives information on the prevailing trip times on all the links of the network. These form the basis for computing the trip times from the user's present location (either at the origin or en-route) to his/her destination along alternative paths. A behavioral assumption is made in the definition of available paths in a corridor network of the type considered here, namely that users perceive and identify a path in terms of its major highway facility, reflecting a hierarchy in the manner in which users perceive a particular network. Thus a path for the purpose of this analysis consists of a single major facility (to the destination) along with its connecting link. Consequently, at any given node (including the origin), the user effectively considers only three paths, on for each facility.

A time constraint is imposed on the actual real-time decisions of the participants in this experiment. At the origin, the participant has a limited time to decide the path he/she will enter. If the time runs out before a response has been supplied by the participant, he/she will enter the pre-assigned highway (default option). During the trip, if the participant is faced with a route switching decision and does not respond within the time limit, he/she will continue on the current route. The decision time constraint is set at 10 seconds to simulate real-life driving time constraint.

Three experimental factors concerning ATIS information quality and credibility are examined in this experiment. The first factor pertains to the nature of information. Two levels are provided for this factor: descriptive and prescriptive. Through the provision of descriptive information, ATIS users are informed of the estimated trip time on every path alternative to the destination when approaching a decision node. Prescriptive information, on the other hand, supplies users only the advice of which highway to take next, simulating an information strategy of individual route.

The second experimental factor is the information quality, with six levels of information type considered here, covering a wide range of information strategies. These levels are specifically designed to follow a hierarchy of accuracy in travel time prediction, from highly precise trip time predictions to randomly generated trip time values. Of course, given the dynamic nature of the simulator, even trip time predictions based on a good prediction mechanism may not always be reliable, though on average the intended direction of hierarchy is preserved.

The first level of this experimental factor provides highly accurate trip times based on travel time prediction on the downstream links. To obtain the predicted information, a traffic probing mechanism has been devised to emit passive "dummy" (or virtual) cars at decision points to travel downstream to the destination. The travel time experienced by these traffic probes are then relayed to the ATIS driver at that decision node as the predicted trip time. Previous simulation experiments have confirmed the ability of this mechanism to produce accurate trip times (Mahmassani and Chen, 1993).

The second level of this experimental factor is prevailing information, where the travel times on the alternative paths from the current decision node are based on prevailing travel times on all the downstream links, similar to the TRAVTEK (or AUTOGUIDE) system. Since this strategy fails to account for the time-dependent nature of travel times on the downstream links, it is generally less accurate than the predicted information. In fact, Mahmassani and Chen (1993) have found this class of information systems not particularly reliable, according to several objective error measures.

The third level of this experimental factor consists of perturbed information, where by random errors are systematically introduced to the predicted travel times predicted using the

same mechanism as the first level. Perturbation is achieved by adding a value randomly drawn from a Normal distribution to the mean of the predicted travel times. A coefficient of variation (standard deviation to mean ratio) of 20% is enforced to ensure that the perturbation remains within a sensible range. This level is intended to reflect field errors due to faulty traffic sensors or interference during transmission.

The fourth and fifth levels of this factor pertain to differential availability of information. Under the fourth level, no information is available to users on one of the three facilities, randomized on each day. The available information is based on prevailing trip times.

Under the fifth level, the differentially supplied information is based on predicted travel times instead. These two levels are intended to capture the influence of partial information on compliance behavior.

The last level of this experimental factor corresponds to completely random information, which serves as the worst case scenario. The ATIS system under this level supplies randomly generated trip times for the three highways at each decision node, entirely independent of the prevailing traffic conditions in the network, designed to provide a benchmark in evaluating user acceptance and compliance to highly imperfect information.

The third factor considered in this experiment is the *ex post* performance feedback by an ATIS system, and consists of three levels of feedback. Under the first level, the information system furnishes feedback on the user's own experience, such as the actual trip time experienced on the chosen path, and the arrival time to work at the end of the trip. In addition to their own experience, users under the second level receive a display of the path recommended by the information system and its associated trip time and arrival time to work. The recommended path here is defined as the path obtained by consecutively selecting at each decision node either the path with the lowest trip time displayed by the system (implicit recommendations) as in descriptive information strategy, or the path advised by the system (explicit recommendations) as in prescriptive information strategy. Note that the recommended path here may not necessarily be the one with the actual minimal trip time. This level allows for a comparison of the choices made by user to the recommendation provided by the information system, through which the information quality of the system is assessed. Under the third level, instead of providing the feedback on the recommended path, the information system provides user feedback on the actual best path (the path with the actual lowest trip time *ex post facto*) and its associated trip time and arrival time to work. This level forms a consistent basis for users to compare their actual decisions to the optimal trip-making choices and to assess the quality of their decisions.

A total of 124 commuters participated in this experiment, in which each participant was asked to commute in four different scenarios. Upon completion of this experiment, 372 complete sets of data were collected, each set corresponding to one scenario and consisting of 4 days (trips).

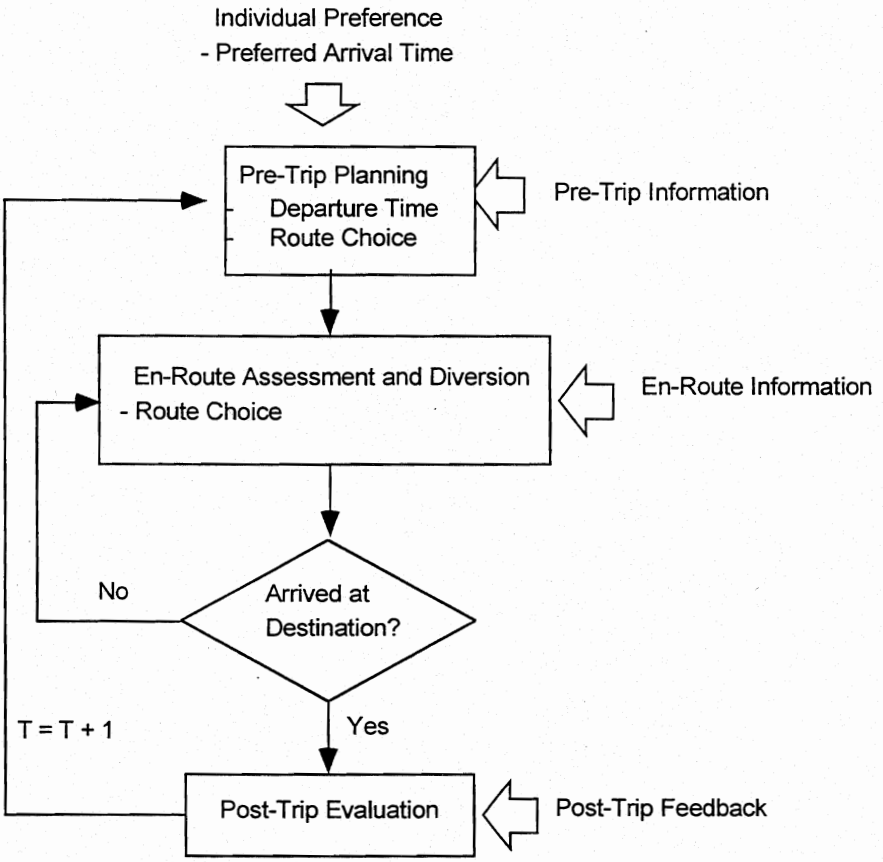


Figure 3.6: Conceptual framework for day-to-day commuting decision process with real-time information

Experimental Procedures

Step 1: Introduction and pre-travel survey

A brief orientation was given to each participant at the beginning of the experiments. After briefing, each subject was asked through the pre-experiment questionnaire, prior to engaging in this interactive experiment, to provide responses to a set of basic questions, including age, gender, occupation, commuting frequencies by driving per week, tolerance to late arrival at work place, and preferred arrival time at work place.

Step 2: Initialization

Initially, each participant was asked to drive through the corridor network with no traffic loaded onto it for as many times as they requested so as to familiarize participants with the network configuration and path capacities at free flow.

Step 3: Pre-Trip Decisions

For each scenario, participants were required to complete four trips to the CBD through the corridor, corresponding to a series of day-to-day morning commutes. Initially (day 1), each participant's time of departure was pre-assigned. When the simulation of the peak period started, each subject was provided with a continuous display of the commuting corridor with the level of congestion on every link in the network updated in real-time and a clock displayed the current (simulated) time on his/her screen (see Figure 3.7). Once a participant's designated departure time was reached, his/her screen displayed all possible paths for him/her to take, together with the expected trip time on each path and the congestion levels in each link represented by different colors (see Figure 3.8). The participant were first asked if they wish to depart now or delay departure to a later time. When they decided to depart for commute, they could point and click using the mouse at links labeled 1, 2, and 3 in right-middle of the display window to select a path to depart his/her origin within the time constraint or the default path was chosen.

Step 4: En-Route Decisions

Once the participant entered the network, he/she received real-time updates of his/her vehicle's position (represented by a green triangle symbol) in the corridor on the screen. When the vehicle arrived to a node where route switching was possible, i.e., crossover links were available, his/her screen displayed all available paths, together with the expected trip time on each path (see Figure 3.2). At the same time, all links emanating from the current node were highlighted on the corridor display. The subject then decided whether to stay on the current route or switch to an alternative route. Furthermore, if the vehicle got stuck in the link-end queue, a warning was displayed in the situation message box to alert the driver (see Figure 3.3).

Step 5: Post-Trip Evaluation

When the participant reached the destination, he/she was supplied with feedback including path history and trip summary statistics, in addition to the departure time, arrival time and total travel time for that commuting day (see Figure 3.9). The participant was then required to choose an intended departure time for the next day, until day 4, after which time the scenario ended.

Step 6: Post-Travel Interview

After the experimental runs had been completed, the subjects participating in the experiment were asked to evaluate the traffic information system for perceived reliability and potential usage through post-travel questionnaire.

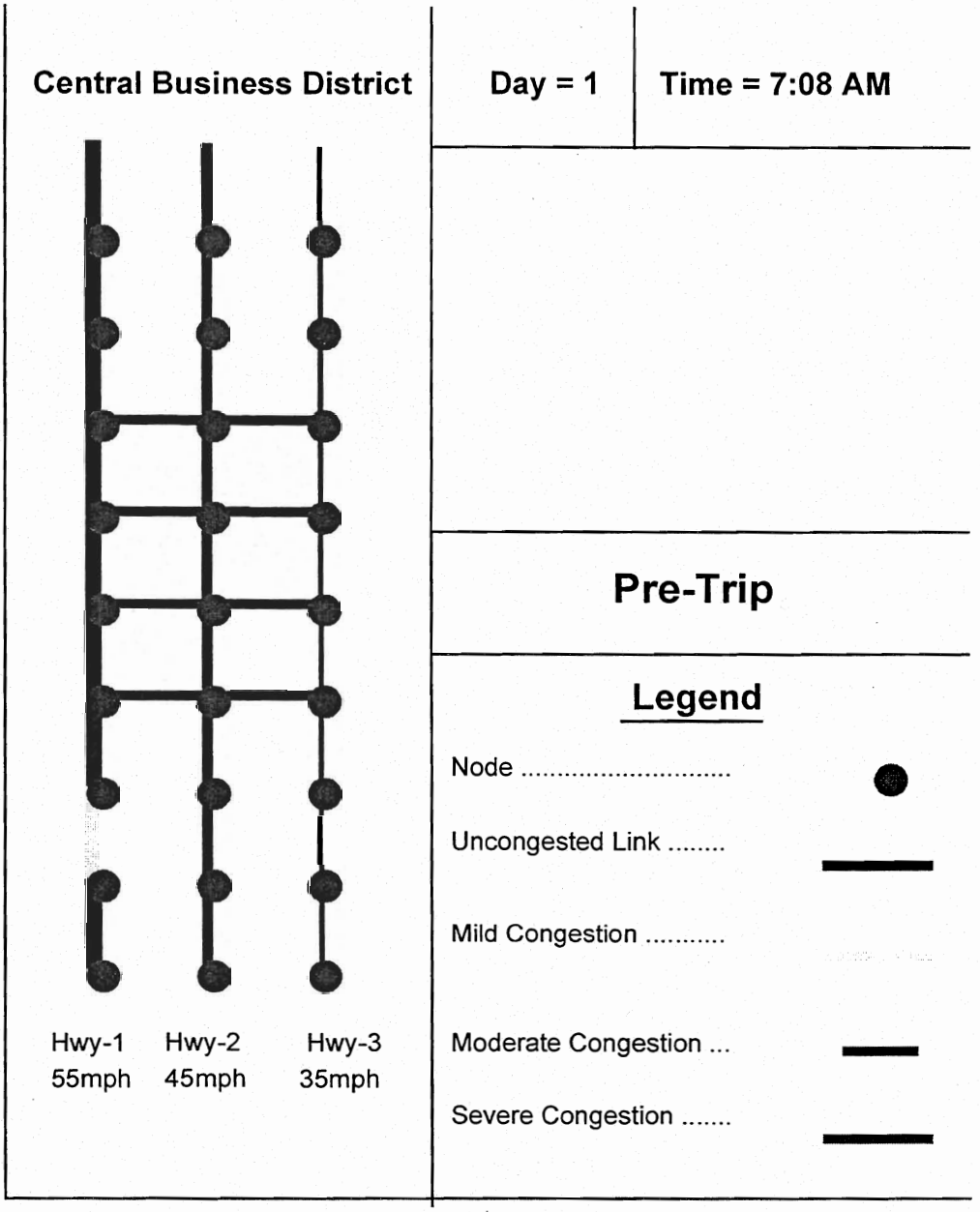


Figure 3.7: Information display before departure

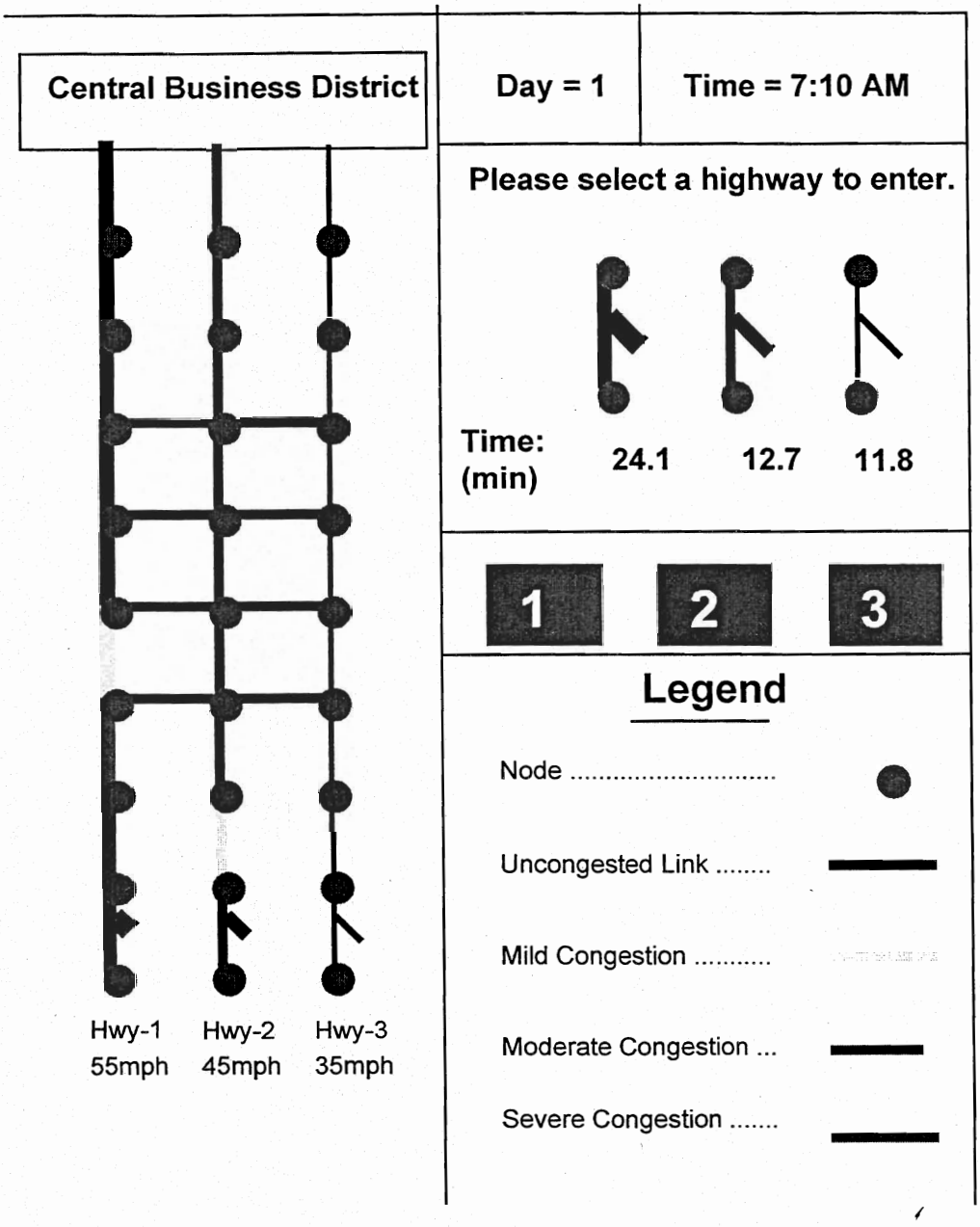


Figure 3.8: Pre-trip path selection information display

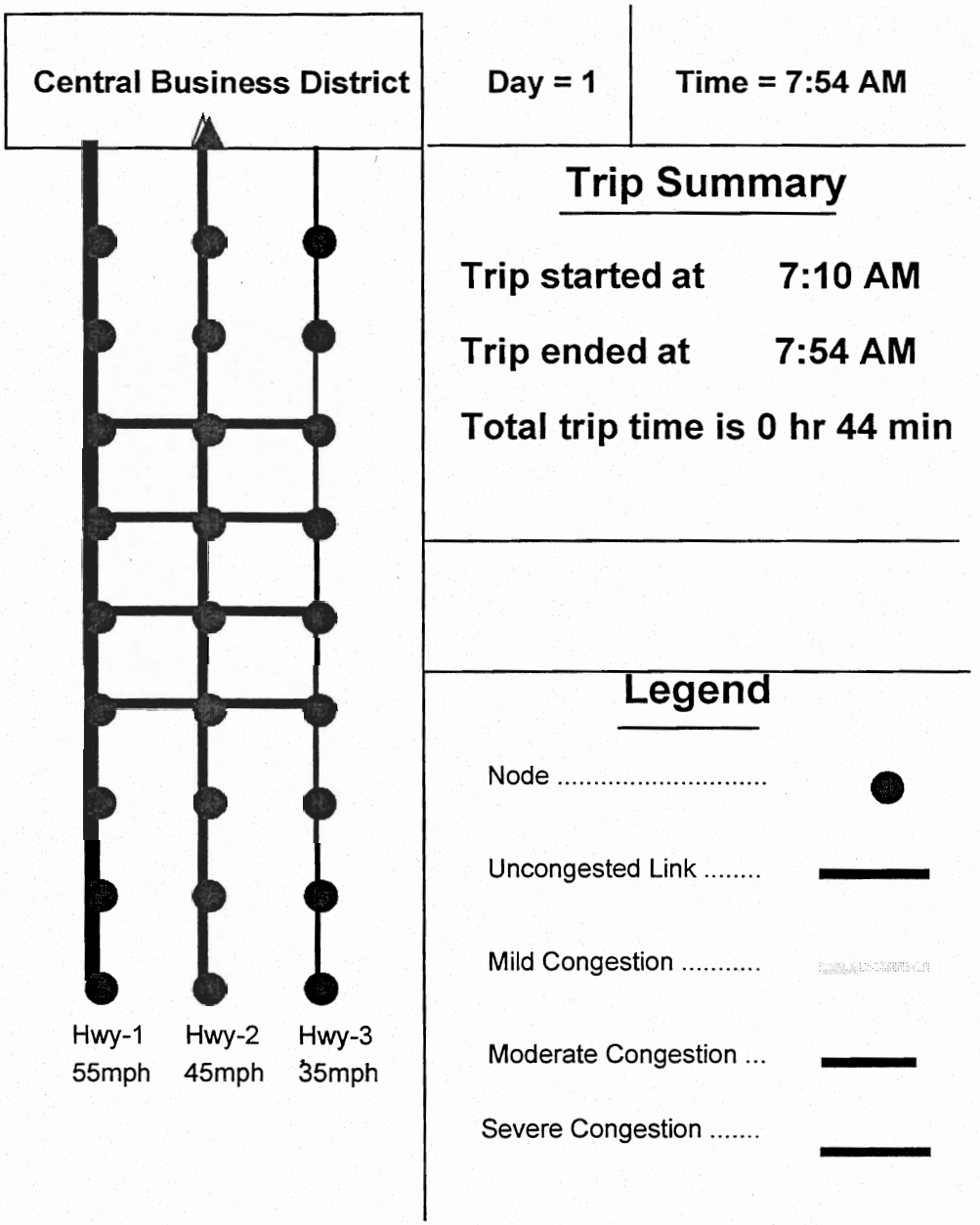


Figure 3.9: Post-trip information display

Subject Recruitment

The recruiting letter explaining the objectives and volunteers' obligations was sent to employees of The University of Texas at Austin via the random sampling technique to obtain their consent for participation. The requirements were that the participant should be a commuter, and has an office on campus. No students were recruited for this experiment. After receiving the

response letters from the volunteers, the participants were arranged to participate in this experiment in the Civil Engineering Learning Resource Center. A total of 124 subjects participated in this experiment.

SUMMARY

This chapter has presented the research methodology for studying dynamics of commuter behavior under real-time traffic information. First, a background review of previous behavioral work at the University of Texas at Austin is provided, namely: (1) interactive experiments for the study of day-to-day dynamics of tripmaker behavior; (2) survey diaries to obtain detailed information about the actual behavior of commuters; and (3) simulation assessments of the ATIS systems in reducing traffic congestion and of the interactions among key factors, such as nature and amount of information, market penetration, congestion severity, and information reliability. This body of work ensures the theoretical validity and physical consistency of the simulator developed and the interactive experiments conducted in this research.

The dynamic interactive simulator is presented next. This simulator offers the capability for real-time interaction with and among multiple driver participants in a traffic network under ATIS. It considers both system performance as influenced by driver response to real-time traffic information and driver behavior as influenced by real-time traffic information based on system performance. This simulator is dynamic in the sense that it actually "simulates" traffic. Its "engine" is a traffic flow simulator and ATIS information generator (DYNASMART), that displays information consistent with the processes actually taking place in the (simulated) traffic system. The decisions made by the driver participants are fed directly to the simulator, and as such influence the traffic system itself and the subsequent stream of information stimuli provided to the participants.

Controlled "laboratory-like" interactive experiments involving real commuters in a simulated traffic system are presented. These experiments involved commuters supplying departure time and route decisions in response to a spectrum of different real-time ATIS strategies of varying degree of information quality in a simulated traffic system using this simulator. By actually simulating traffic conditions in response to the supplied commuter decisions, the simulator provided stimuli to the participants that were always consistent with physically realistic traffic behavior, and with their previous actions.

CHAPTER 4: THEORETICAL FRAMEWORK

INTRODUCTION

As indicated in Chapter 3, the methodology for user behavior research of this nature consists of two parts:

(1) observation of actual driver behavior through interactive, laboratory-like experiments, and

(2) analysis of data collected and modeling of driver behavior.

This chapter discusses the modeling frameworks developed to study commuters' trip-making behavior in response to different information strategies of varying information quality and credibility. Of particular relevance are the effects of these strategies on the behavior of user compliance to the information supplied and of overall user satisfaction over time as they become more familiar with the traffic system and the information received, as it is critical to the successful deployment of the information technology in achieving traffic control objectives. Commuters' day-to-day departure time and route decision processes under these strategies are analyzed as well, following the modeling framework developed by Mahmassani and Liu (1997).

Poisson regression models are employed to capture the principal effects of the characteristics of the information supplied, the performance of the traffic system, as well as the commuters' experience with the traffic system and with the real-time information on commuter compliance and satisfaction behavior. Furthermore, multinomial probit models of discrete choice dynamics including pre-trip departure time and path decisions as well as en-route route switching choices are calibrated. By estimating these models using the experimental data, substantive hypotheses regarding the factors influencing the commuter behavior in response to different real-time information strategies of varying information quality and credibility are tested.

The conceptual and methodological aspects of these models are described in the rest of this chapter and they are organized as follows. The first section defines the user compliance and satisfaction frameworks. The next section provides a background discussion of Poisson regression models, followed by the modeling descriptions of user compliance and satisfaction. Tests of data under- and over-dispersions are presented including modeling alternatives. A background of the decision model of bounded rationality is discussed next. The next section reviews the estimation procedure for the multinomial probit models. The modeling description of indifference band of joint switching decisions is then discussed followed by a summary of the chapter.

COMPLIANCE AND SATISFACTION MODELING FRAMEWORK

User compliance and satisfaction are two aspects of tripmaker behavior and response to real-time traffic information that are critical to the successful deployment of information technology in achieving traffic control objectives. Very limited research effort has been devoted to the understanding of these behavioral aspects, however, leaving this area of concern inadequately addressed. Of particular interest is the compliance behavior with respect to trip-making decisions, both pre-trip and en-route, as well as the user satisfaction in regard to diminishing propensity to switch either departure time or route over time. While there have been a flurry of published studies of user satisfaction processes in conventional consumer behavior research, notably by the works of LaTour and Peat (1980), Oliver and Beardon (1983), and LeBarbera and Mazursky (1983), literature review to date shows only one related study in the domain of ATIS driver behavior research: driver en-route guidance compliance at intersections (Chen and Jovanis, 1997).

Poisson regression models are employed to capture the principal effects of the characteristics of the information strategies, the traffic system and the commuters, on the observed frequency of decisions to comply and follow traffic information received per trip, as well as that of decisions to not modify departure time and route choices before trip and to not divert en route. These are indirect approaches that focus on the frequency of compliance and satisfaction decisions and relate such decisions to the characteristics of the information supplied, the performance of the traffic system, as well as the commuters' own experience. The estimation results of these models will provide useful insights into the development of a model that will encompass both the explanation and prediction of user compliance and satisfaction behavior under the provision of real-time information, and the tools and guidelines for ensuring that any ATIS design and development process leads to an effective and satisfactory product.

Background for Poisson Regression (Frequency) Model

Poisson regression models of count data have been applied to driver accidents (Weber, 1971), highway fatalities (Michener and Tighe, 1992), and trip generation modeling (Ruygrok and van Essen, 1980). Furthermore, Mannering (1989) used this class of models to investigate the determinants of commuter flexibility in changing routes or departure times for the morning trip to work. Two models were developed to treat departure time and route changes separately. Hatcher (1991) expanded the Poisson regression methodology to two types of decisions, the frequency of stops observed during morning and evening commutes, and the frequency of departure time, route, and joint switches, for a sample of Austin commuters. The same model specifications were further applied by Jou (1994) to the Dallas area.

To assess user compliance and satisfaction behavior under real-time traffic information, Poisson regression models are developed to model the frequency of compliance decisions with information received and non-switching decisions due to satisfactory trip-making experience and expectations. Central to the modeling analysis is the behavioral assertion that, with the introduction of real-time information, tripmakers would experiment and search for opportunities to improve their commuting trips. With other tripmakers experimenting and searching as well, and the collective effect of their dynamic interactions on the traffic system as whole, tripmakers would most likely never completely converge to a satisfactory departure time and route. Nor would they be fully compliant to traffic advisory, granted that in this complex traffic system, no prediction methodology could be absolutely accurate and reliable. In light of the dynamic nature of the system, together with the randomness inherent in decision-making behavior, the Poisson distribution provides a reasonable description of both the number of compliance instances and the number of non-switches by a commuter.

Poisson models assume an equal number of "trials" for all commuters and are particularly well suited to the present experiment design, in which each subject has a fixed number of 5 decision nodes (one pre-trip and four en-route) per trip. A detailed description of the experimental design is provided in Section 3.4.

Following the standard Poisson model, the probability of a commuter *i* making c_i compliance decisions per trip is given by

$$P(c_i) = \frac{\exp(-\lambda_i)\lambda_i^{c_i}}{c_i!} \tag{4.1}$$

where λ_i is the expected frequency of compliance decisions per trip for commuter *I*, i.e., $\lambda_i = E[c_i]$.

To estimate Poisson models, maximum likelihood estimation procedure is used. Assuming a specification of the form

$$\log \lambda_i = \beta \mathbf{X}_i \tag{4.2}$$

where β is a vector of estimable parameters and $\mathbf{X}_i$ is a vector of socio-economic and commuting characteristics for commuter *i*. The likelihood function from equations. (4.1) and (4.2) is

$$L(\beta) = \prod_i \frac{\exp[-\exp(\beta\mathbf{X}_i)][\exp(\beta\mathbf{X}_i)]^{c_i}}{c_i!} \tag{4.3}$$

which yields the log-likelihood function of

$$\log L(\beta) = \sum_i [-\log c_i! - \exp(\beta \mathbf{X}_i) + c_i \beta \mathbf{X}_i] \quad (4.4)$$

with gradient

$$\frac{\partial \log L}{\partial \beta'} = \sum_i [c_i \mathbf{X}_i - \mathbf{X}_i \exp(\beta \mathbf{X}_i)] \quad (4.5)$$

and Hessian

$$\frac{\partial \log L}{\partial \beta' \partial \beta} = \sum_i [-(\mathbf{X}_i \mathbf{X}_i' \exp(\beta \mathbf{X}_i)] \quad (4.6)$$

The above methodology is also applied to model the frequency of non-switchings of joint departure time and route as a measure of user satisfaction. A detailed description of the procedures and theoretical background for the Poisson regression can be found in Lerman and Gonzalez (1980).

Rate of Compliance with ATIS

In the context of our laboratory experiments, tripmakers' compliance behavior under real-time traffic information can be quantified using the observed frequency of commuter decisions to comply with or accept traffic advisory. Instead of restricting to prescriptive or normative information and guidance only, we have relaxed the definition of traffic advisory to include descriptive information on alternative paths, as long as there is an implied "best" path or recommendation to be followed. This measure of compliance can be applied to pre-trip path decisions as well as en-route route diversions, and for the purpose of studying compliance behavior at the trip level, both choice dimensions have been included in our models.

The choice dimension of departure time decisions is not considered in our compliance framework because none of the information strategies in the experiment simulate departure time advice provision, either in the form of trip time profile against a departure time scale or an individually-optimized departure time adjustment advisory. It should be noted, nevertheless, that the three feedback mechanisms, included as a factor in the experimental design, could conceivably give commuters a basis for departure time adjustment through trial and error from day to day.

Of particular interest to us is the association between compliance and switching decisions. A decision to comply with real-time traffic information on available paths to destination does not always constitute a switch to an alternative route and vise versa. It depends on whether the path the commuter is currently on is the "best" path, as suggested by the real-time information. If his/her current path is indeed the " best" path, then the decision to remain on the current path complies with the information received. Alternatively, by switching to the "best" path when the commuter's current path is not the "best" path, he/she has complied. Based on the dynamic

switching models developed by Mahmassani and Liu (1997), the accuracy and reliability of real-time information is one of the main determinants governing commuters' decision-making processes for pre-trip and en-route path switches. Of particular interest here is in testing the significance of this determinant in their compliance decision-making processes. Furthermore, the indifference bands observed in the boundedly rational switching framework can be interpreted as a "cost" of switching to the tripmakers. This "cost" of switching will be another factor to be investigated under the compliance modeling framework.

Poisson frequency models of this kind can provide useful insights into the development of a dynamic decision model that can be used to explain and predict user compliance behavior under ATIS, which is particularly applicable to the evaluation of the effectiveness of real-time information provision in achieving traffic control objectives.

Trip Satisfaction and Its Evolution Trends under ATIS

There are two outcomes of trip-making under the influence of real-time traffic information which can strongly affect future behavior: (1) satisfaction or (2) dissatisfaction. A commuter starts a routinized trip with certain expectations about what real-time information will assist in improving daily trip performance. Satisfaction is the hoped-for outcome. Satisfaction is defined as a reduction of changes in trip-making decisions over time as a result of post-trip evaluation, confirming the outcome of these decisions to be consistent with prior beliefs and expectations. Dissatisfaction, of course, is the outcome when this confirmation does not take place.

Trip-making decisions considered here includes pre-trip departure time and route choices, as well as en-route route diversions. Dissatisfaction in this regard, is usually gauged by the frequency of commuter decisions to switch either departure time or route, both pre-trip and en-route (Mannering, 1989; Mahmassani and Hatcher, 1992; Jou, 1994). Conversely, satisfaction behavior can be measured by the observed frequency of trip-making decisions in which drivers are satisfied with the current commuting conditions and do not wish to modify or switch either departure time or route, both pre-trip and en-route. Route switching decisions here, however, are defined differently from previous studies. Under this user satisfaction framework, we recognize the possibility that a commuter may learn over time, through his/her experience with the traffic system and the real-time information received, to perceive a commuting route that consists of segments from different highways. Thus, a route switch under this modeling framework is defined as a deviation from the route choice made from the previous day for that particular segment the commuter is traversing.

Previous studies focusing on the day-to-day and/or real-time dynamics of urban commuter behavior have established past travel experiences as a crucial criterion in determining commuters' departure time and route switching decisions (Mahmassani and Chang, 1985 and

1987; Mahmassani and Stephan, 1988; Tong, 1990; Mahmassani and Jou, 1996; Mahmassani and Liu, 1996). One of the objectives is to evaluate how and to what extent this past experience affects user satisfaction under our framework. In addition, there may be trends of switching/non-switching behavior over time by which the traffic system may be impacted, especially during the earlier stages of ATIS introduction. It is, therefore, another objective to test the existence of a more desirable trend of commuters' diminishing propensity to switch either departure time or route as a consequence of confirmation of satisfying outcomes over time, particularly when experienced with information of varying qualities.

Alternative Models for Under- and Over-Dispersion

The Poisson regression model is restrictive in several ways. First, it is based on the assumption that events occur independently over time, which may break down if there is dynamic dependence between the occurrence of successive events. Prior occurrence of an event, such as an accident or illness, may raise the probability of subsequent occurrence of the same or similar event (Heckman and Borjas, 1980). Another mode of dynamic interdependence is inherent in the notion that events occur in "spells" and the spells themselves occur according to some probability function, whereas the events within a given spell, which occur according to a different probability function, may be dependent (Cresswell and Froggatt,1963). Second, it is based on the assumption that the variance and the conditional mean are equal. This assumption may fail to account for either under- or over-dispersion of the data. For our study, it is desirable to test the Poisson restriction and to relax it if appropriate.

Several tests for under- and over-dispersion have been proposed by Cameron and Trivedi (1986). Probably the simplest, and by their comparative study results, the optimal test involves least-squares regression. The testing framework is built around the hypothesis that for the Poisson model, $\{(y - E[y])^2 - E[y]\}$ has mean zero, and it can be set up as follows:

$$H_o : \mathrm{var}[y_i] = \mu_i$$

vs. $$H_a : \mathrm{var}[y_i] = \mu_i + \alpha * g(\mu_i) \qquad (4.7)$$

The test Cameron and Trivedi propose is carried out by testing the significance of the single coefficient in the linear ordinary least square regression of

$$Z_i = [(y_i - \mu_i)^2 - y_i] / (\sqrt{2\mu_i}) \qquad (4.8)$$

on $$w_i = g(\mu_i) / (\sqrt{2\mu_i}) \qquad (4.9)$$

The advantage of this test as proposed by Cameron and Trivedi is that the model need only be estimated under H_o. There are two possibilities suggested for $g(\mu_i), \mu_i$ or μ_i^2.

One way to relax the Poisson restriction is to allow for unexplained randomness in λ_i by replacing equation (4.2) by the stochastic equation

$$\text{Log } \lambda_i = \beta \mathbf{X}_i + \varepsilon_i \qquad (4.10)$$

where the error term could reflect a specification error such as unobserved omitted exogenous variables, allowing the variance of the process to differ from the mean. The probability density function for ε_i can assume various parametric forms, most commonly as the gamma, by which the resulting model belongs to the negative binomial family. Assuming a gamma distribution of mean 1.0 and variance α^2, the resulting probability distribution is

$$P(c_i | \varepsilon_i) = \frac{\exp[-\lambda_i \exp(\varepsilon_i)][\lambda_i \exp(\varepsilon_i)]^{c_i}}{c_i!} \qquad (4.11)$$

Integrating ε_i out of this expression produces the unconditional distribution of c_i. The formulation of this distribution which is used in maximum likelihood estimation is

$$P(c_i) = \frac{\Gamma(\theta + c_i)}{[\Gamma(\theta) * c_i!]} * \mu_i^{\theta} (1 - \mu_i)^{c_i} \qquad (4.12)$$

where $\mu_i = \theta / (\theta + \lambda_i)$ and $\theta = 1/\alpha$, such that

$$\text{var}(c_i) = E[c_i]\{1 + \alpha E[c_i]\} \qquad (4.13)$$

The α in equation (4.13) is a measure of dispersion and if both the model under H_o and the model under H_a in (4.7) are estimated by maximum likelihood, and the model under H_o is derived from the model under H_a by this single parametric restriction α, then the negative binomial is the correct choice of model for α to be significant and the Poisson model is inappropriate.

The maximum likelihood procedure for estimating negative binomial models is as follows:

$$\text{Log } P(c_i) = \log\Gamma(\theta + c_i) - \log\Gamma(\theta) - \log c_i! + \theta \log \mu_i + c_i \log(1 - \mu_i) \qquad (4.14)$$

where $\theta = 1/\alpha$

and $\mu_i = \theta / (\theta + \lambda_i)$

A simplication can be achieved by eliminating the gamma functions since

$$\Gamma(\theta + c_i) = (\theta + c_i - 1)\Gamma(\theta + c_i - 1) \qquad (4.15)$$

By recursion,

$$\Gamma(\theta + c_i) = \Gamma(\theta)\prod_{j=0}^{c-1}(\theta + j) \tag{4.16}$$

Taking the logs eliminates the two gamma integrals. Consequently,

$$\log P(c_i) = \sum_{m=0}^{j-1}\log(\theta + m) - \log c! + \theta \log \mu_i + c_i \log(1 - \mu_i) = \log L_i \tag{4.17}$$

and the derivatives for the negative binomial regression model are:

$$\partial \log L_i / \partial \lambda_i = [\theta / \mu_i - c_i /(1 - \mu_i)]\partial \mu_i / \partial \lambda_i \tag{4.18}$$

$$\partial \log L_i / \partial \beta = [\theta /(1 - \mu_i) - c_i / \mu_i]X_i \tag{4.19}$$

$$\partial \log L_i / \partial \theta = \sum_{j=0}^{c-1} 1/(\theta + j) + \log \mu_i + (1 - \mu_i) - c_i \mu_i / \theta \tag{4.20}$$

Negative binomial regression models of count data have been applied to study rural freeway and urban intersection traffic accidents (Shankar, Mannering, and Barfield, 1995; Poch and Mannering, 1996), and health inspections by the Occupational Safety and Health Administration (OSHA) (Gary and Jones, 1991). For more generalized event count (GEC) models, readers are referred to King (1989).

BOUNDED RATIONALITY MODELING FRAMEWORK FOR DEPARTURE TIME AND ROUTE SWITCHING DECISIONS

Following the modeling framework developed by Mahmassani and Liu (1997), dynamic multinomial probit (MNP) choice models, including pre-trip departure time and path decisions as well as en-route route switching choices are calibrated to investigate the effects of different information systems of varying information quality and credibility. This framework is based on the notion of bounded rationality (and the associated satisficing rule), originally proposed by Simon (1955; 1956). This framework had been extensively tested and validated by Mahmassani and co-workers (Mahmassani and Chang, 1985, 1987; Mahmassani and Stephan, 1988; Tong, 1990; Mahmassani and Jou, 1996) in the context of the day-to-day dynamics of departure time and route decisions of urban commuters as well as for the real-time route switching decisions under in-vehicle information by Mahmassani and Jayakrishnan (1991). The notion of bounded rationality was operationalized in this context in the form of "indifference bands" within which users are satisfied and do not switch from their current selection.

The main objective here is to investigate how and to what extent different real-time information designs of varying degree of information quality and credibility affect the travel behavior of commuters under this framework of joint departure time and route switching

decisions. A concise yet comprehensive description of this framework is provided in this section. For a more detailed discussion of this particular framework, readers are referred to Mahmassani and Liu (1997).

Background for Estimating Multinomial Probit Model

The multinomial probit (MNP) model, in which the error terms are jointly multivariate normal (MVN) distributed with zero mean and a general variance-covariance matrix, is employed here to provide mathematical representations of discrete choice situations that incorporate bounded rationality behavioral theory. With a general variance-covariance structure, the MNP model can capture dynamic aspects of decision-maker choice behavior, including state dependence, contemporaneous and serial correlation, as well as taste variation.

The calculation of the choice probability of a sequence of travel decisions (including daily departure time at the origin and route selections both pre-trip and en-route), however, requires the evaluation of the multidimensional integral of the multivariate normal density function for which there is no closed form solution when the number of alternatives exceeds three. Several methods have been proposed to evaluate MNP choice probabilities, including (1) approximation methods, such as Clark's (1961), Mendell-Elston (1974), and Langdon's separated split approximation (1984), (2) numerical integration, such as Hausman and Wise (1978), and (3) Monte-Carlo simulation (Albright, Lerman and Manski, 1977; Lam, 1991).

CHOMP (Choice Modeling Program) developed by Daganzo and Schoenfeld (1978) is the first MNP estimation tool using Clark's approximation method to evaluate MNP choice probabilities. Tong (1990) has specified and estimated multinomial probit models for departure time and route indifference bands using CHOMP. However, the accuracy of CHOMP is questionable when the dimension of the integral is high. It was not possible to estimate correct models with more than 4 or 5 alternatives. A multinomial probit model estimation program, based on Monte-Carlo simulation and new implementations of quasi-Newton BFGS (Broyden-Fletcher-Goldfarb-Shanno) nonlinear optimization procedure with a backtracking line search method, has been shown to calibrate MNP models with general variance-covariance matrix structure and a relatively large number of choice alternatives accurately and efficiently (Lam, 1991). This estimation program has been successfully applied to the estimation of dynamic travel behavior models with up to 17 alternatives in a parallel supercomputing environment (Mahmassani and Jou, 1996). An extension of this procedure to estimate a dynamic generalized ordinal probit model was implemented by Yen (1994) to calibrate dynamic models of telecommuting adoption processes.

Nonetheless, two major limitations were indicated by Lam (1991) in his study. First, the mathematical properties of the MNP model do not guarantee convergence to a global maximum

likelihood estimate (MLE), and the solution obtained by his MNP estimation program critically depends on the location of the initial points, which are chosen arbitrarily. It is very difficult to arbitrarily choose a "good" starting point when the number of parameters to be estimated is large, such as in dynamic behavioral models. Second, it is essential to maintain a positive definite variance-covariance matrix in the estimation process to evaluate the MNP choice function, but this becomes problematic with very general error term structures. Furthermore, certain model specifications for real-time route switching decisions, such as that proposed by Mahmassani and Jayakrishnan (1991), could not be estimated directly using the MNP estimation program developed by Lam.

A MNP estimation program using genetic algorithms (GAs) to search for a global optimum in maximum likelihood estimation while maintaining a positive definite variance-covariance matrix in evaluating the MNP choice probabilities has been developed by Mahmassani and Liu (1997). In this procedure, the GAs search globally for the initial solutions that maintain a positive definite variance-covariance matrix, and nonlinear programming techniques are used to fine-tune the results in conjunction with the global search. The estimation of dynamic MNP models of joint departure and route switching decisions presented in this report was made possible by this program.

Joint Indifference Band for Departure Time and Route Switching Decisions. The boundedly-rational mechanism governing day-to-day departure time switching decisions postulates that commuter i does not switch his/her next day's departure time so long as the corresponding schedule delay SD_{it} on the current day t, which is the difference between preferred arrival time PAT_i and actual arrival time AT_{it}, remains within the user's indifference band for departure time choice IBD_{it} (with different components EBD_{it} and LBD_{it} for early and late arrivals, respectively), as follows:

$$SD_{it} = PAT_i - AT_{it} = ESD_{it}, \text{ if } SD_{it} \geq 0$$
$$= LSD_{it}, \text{ if } SD_{it} < 0 \qquad t = 1, 2, \ldots, T \qquad (4.21)$$

$$\delta_{it} = -1, \quad \text{if } 0 \leq ESD_{it} \leq EBD_{it} \text{ or } -LBD_{it} \leq LSD_{it} \leq 0$$

$$\delta_{it} = 1, \quad \text{otherwise} \qquad (4.22)$$

ESD_{it} and LSD_{it} denote the early-side and the late-side schedule delay, respectively. The variable δ_{it} is a departure time switching decision indicator variable, which equals 1 when user i switches departure time after the commute on day t-1; δ_{it} equals -1 otherwise. EBD_{it} and LBD_{it} are the respective departure time indifference bands of tolerable schedule delay corresponding to

early and late arrivals (relative to PAT_i) for day t. These are latent quantities modeled as random variables with systematic and random components given by:

$$EBD_{it} = f_e(X_i, Z_{it}, \theta_{it}) + \tau_{it,e} \qquad \tau_{it,e} \sim MVN(0, \Sigma_{\tau e})$$

$$LBD_{it} = f_l(X_i, Z_{it}, \theta_{it}) + \tau_{it,l} \qquad \tau_{it,l} \sim MVN(0, \Sigma_{\tau l}) \qquad (4.23)$$

The subscripts 'e' and 'l' represent the early-side and late-side indifference bands, respectively. The systematic components of the early-side and late-side indifference bands for departure time are $f_e(\cdot)$ and $f_l(\cdot)$, respectively. The vector of user characteristics X_i and the vector of performance characteristics Z_{it} capture user i's inherent attributes and experience up to day t, respectively; θ_{it} is a vector of parameters to be estimated. The random terms $\tau_{it,e}$ and $\tau_{it,l}$ are assumed to be normally distributed over days and across commuters with zero means and general covariance structure.

The departure time indifference band with early-side and late-side components can be written in compact form for joint estimation purposes by introducing a binary indicator variable $\square_{it}$, which equals 1 if $SD_{it} = ESD_{it} > 0$ (early-side), and 0 if $SD_{it} = LSD_{it} < 0$ (late-side).

$$IBD_{it} = \omega_{it} EBD_{it} + (1-\omega_{it}) LBD_{it}$$

$$= \omega_{it} f_e(X_i, Z_{it}, \theta_{it}) + (1-\omega_{it}) f_l(X_i, Z_{it}, \theta_{it}) + \omega_{it} \tau_{it,e} + (1-\omega_{it}) \tau_{it,l} \qquad (4.24)$$

Letting $f(X_i, Z_{it}, \theta_{it}) = \omega_{it} f_e(X_i, Z_{it}, \theta_{it}) + (1-\omega_{it}) f_l(X_i, Z_{it}, \theta_{it})$

and $\tau_{it} = \omega_{it} \tau_{it,e} + (1-\omega_{it}) \tau_{it,l}$

we obtain: $IBD_{it} = f(X_i, Z_{it}, \theta_{it}) + \tau_{it} \qquad (4.25)$

The same bounded rationality notion is used here for initial route selection and en-route path switching. Commuter i does not switch route or path so long as the corresponding trip time saving TTS_{ijt} (at decision node j on day t), which is the trip time difference between the current path TTC_{ijt} (from decision node j to the destination on day t) and the best path TTB_{ijt} (the shortest path from decision node j to the destination on day t), remains within the commuter's route indifference band IBR_{ijt}, as follows:

$$TTS_{ijt} = TTC_{ijt} - TTB_{ijt} \geq 0; \qquad j = 1, 2, 3, 4, 5$$

$$t = 1, 2, \ldots, T \qquad (4.26)$$

$$\phi_{ijt} = -1, \qquad \text{if } 0 \le TTS_{ijt} \le IBR_{ijt}$$

$$\phi_{ijt} = 1, \qquad \text{otherwise} \qquad (4.27)$$

The subscript j represents the decision node location; j=1 represents initial route selection at the origin and j = 2, 3, 4, 5 represent en-route path switching nodes (Figure 3.5). The variable ϕ_{i1t} is the route switching decision indicator variable, which equals 1 when user i switches initial route on day t after the commute on day t-1, and ϕ_{i1t} equals -1 otherwise; ϕ_{ijt} (j = 2, 3, 4, 5) equals 1 when user i switches his/her path en-route at decision node j, with ϕ_{ijt} equal to -1 otherwise. IBR_{ijt} is the indifference band for initial route selection and en-route path switching corresponding to user i at decision node j on day t.

Following the model proposed by Mahmassani and Jayakrishnan (1991) and implemented in DYNASMART (Jayakrishnan, Mahmassani and Hu, 1994), the following equation has been adopted in the user decision component for both initial route selection and en-route path switching.

$$\phi_{ijt} = -1, \qquad \text{if } TTC_{ijt} - TTB_{ijt} \le \max [\eta_{ijt} TTC_{ijt}, \pi_{ijt}]$$

$$\phi_{ijt} = 1, \qquad \text{otherwise} \qquad (4.28)$$

where

$$\eta_{ijt} = g_r (X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,r} \qquad \xi_{ijt,r} \sim MVN(0, \Sigma_{\xi r})$$

$$\pi_{ijt} = g_m (X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,m} \qquad \xi_{ijt,m} \sim MVN(0, \Sigma_{\xi m}) \qquad (4.29)$$

η_{ijt} represents the relative indifference band, as a fraction of the TTC (trip time along the current path) from decision node j to the destination for user i to switch from the current path on day t; π_{ijt} denotes the minimum trip time saving, from decision node j to the destination, necessary for user i to switch from the current path on day t. Both quantities are latent variables, modelled as random variables, with mean values anticipated to vary systematically with the user's characteristics and experience to date. As such, they consist of both systematic and random components.

In equation (4.29), the subscripts 'r' and 'm' represent the relative indifference band and the minimum trip time saving, respectively. The systematic components of the relative indifference band and the minimum trip time saving are $g_r(\cdot)$ and $g_m(\cdot)$, respectively. The vector of user

characteristics X_i and the vector of performance characteristics Z_{ijt} capture user i's experience up to decision node j on day t; θ_{ijt} is a vector of parameters to be estimated. The random terms $\xi_{ijt,r}$ and $\xi_{ijt,m}$ are assumed to be normally distributed, along five decision nodes over days and across commuters, with zero means and general variance-covariance matrix $\Sigma_{\xi r}$ and $\Sigma_{\xi m}$, respectively.

Comparing equations (4.27) and (4.28), the expression of the indifference band for initial route selection and en-route path switching is obtained as follows:

$$IBR_{ijt} = \max [\ \eta_{ijt} TTC_{ijt},\ \pi_{ijt}\ ] \qquad (4.30)$$

A binary indicator variable W_{ijt} is introduced to represent two different subsets of decisions, depending on which of the corresponding two components of IBR_{ijt} is larger, and thereby governs the decision. W_{ijt} equals 0 if $IBR_{ijt} = \pi_{ijt}$ (i.e., $\eta_{ijt} TTC_{ijt} < \pi_{ijt}$); W_{ijt} equals 1 if $IBR_{ijt} = \eta_{ijt} TTC_{ijt}$ (i.e., $\eta_{ijt} TTC_{ijt} > \pi_{ijt}$). Therefore, equation (4.30) can be rewritten to:

$$\begin{aligned} IBR_{ijt} &= W_{ijt}\, \eta_{ijt} TTC_{ijt} + (1-W_{ijt})\, \pi_{ijt} \\ &= W_{ijt}\, TTC_{ijt} [g_r(X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,r}] + (1-W_{ijt})[g_m(X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,m}] \\ &= W_{ijt}\, TTC_{ijt}\, g_r(X_i, Z_{ijt}, \theta_{ijt}) + (1-W_{ijt})\, g_m(X_i, Z_{ijt}, \theta_{ijt}) + \\ &\quad W_{ijt}\, TTC_{ijt}\, \xi_{ijt,r} + (1-W_{ijt})\, \xi_{ijt,m} \end{aligned} \qquad (4.31)$$

Letting

$$\xi_{ijt} = W_{ijt}\, TTC_{ijt}\, \xi_{ijt,r} + (1-W_{ijt})\, \xi_{ijt,m} \qquad (4.32)$$

and

$$g(X_i, Z_{ijt}, \theta_{ijt}) = W_{ijt}\, TTC_{ijt}\, g_r(X_i, Z_{ijt}, \theta_{ijt}) + (1-W_{ijt})\, g_m(X_i, Z_{ijt}, \theta_{ijt}) \qquad (4.33)$$

then equation (3.17) can be simplified to:

$$IBR_{ijt} = g\,(X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt} \qquad (4.34)$$

A 6Tx6T (where T is the number of decision days included in the sample of observations) variance-covariance matrix for joint departure time and route switching decisions under real-time information, Σ (joint1), can capture serial correlation due to the persistence of unobservable attributes across the sequence of departure time choice, and initial route selection as well as en-route path switching decisions made by the same user. The full variance-covariance structure of

the error terms for departure time and route decisions, Σ(joint1), can be rewritten in matrix form and shown in equation (4.35). A general variance-covariance structure proposed for this study can be found in Appendix B.

	Day 1						. .	Day T					
Departure Time	σ_D^2	γ_{D1}	γ_{D2}	γ_{D2}	γ_{D2}	γ_{D2}		γ_D	0	0	0	0	0
Pre-Trip (Route)	γ_{D1}	σ_1^2	γ_2	γ_2	γ_2	γ_2		0	γ_1	0	0	0	0
En-route (Route)	γ_{D2}	γ_2	σ_2^2	γ_3	γ_3	γ_3	. .	0	0	γ_4	0	0	0
En-route (Route)	γ_{D2}	γ_2	γ_3	σ_2^2	γ_3	γ_3		0	0	0	γ_4	0	0
En-route (Route)	γ_{D2}	γ_2	γ_3	γ_3	σ_2^2	γ_3		0	0	0	0	γ_4	0
En-route (Route)	γ_{D2}	γ_2	γ_3	γ_3	γ_3	σ_2^2		0	0	0	0	0	γ_4

Departure Time	γ_D	0	0	0	0	0		σ_D^2	γ_{D1}	γ_{D2}	γ_{D2}	γ_{D2}	γ_{D2}
Pre-Trip (Route)	0	γ_1	0	0	0	0		γ_{D1}	σ_1^2	γ_2	γ_2	γ_2	γ_2
En-route (Route)	0	0	γ_4	0	0	0	. .	γ_{D2}	γ_2	σ_2^2	γ_3	γ_3	γ_3
En-route (Route)	0	0	0	γ_4	0	0		γ_{D2}	γ_2	γ_3	σ_2^2	γ_3	γ_3
En-route (Route)	0	0	0	0	γ_4	0		γ_{D2}	γ_2	γ_3	γ_3	σ_2^2	γ_3
En-route (Route)	0	0	0	0	0	γ_4		γ_{D2}	γ_2	γ_3	γ_3	γ_3	σ_2^2

(4.35)

Based on the assumption that the pre-trip decision process is different from the en-route decision process, the covariance terms between departure time and pre-trip route decisions are different from those between departure time and en-route path decisions (e.g., E (τ_{it}, ξ_{i1t}) = γ_{D1}, E (τ_{it}, ξ_{ijt}) = γ_{D2}, j = 2, 3, 4, 5). A summary of the error structure for joint departure time and route (including pre-trip and en-route route selections) switching indifference band can be found in Appendix C.

With the formulations of both departure time and route indifference bands described in equations (4.24) and (4.31), the probability of an outcome (δ_{it}, ϕ_{ijt}, j= 1, 2, 3, 4, 5) for individual i at a specific decision node j, after the commute on day t, is given by:

Pr(δ_{it}, ϕ_{ijt}, j = 1, 2, 3, 4, 5)

= Pr {δ_{it} [ω_{it} (ESD_{it} - EBD_{it}) + (1-ω_{it})(-LSD_{it} - LBD_{it})] $\geq$ 0, and

ϕ_{ijt} $(TTS_{ijt} - IBR_{ijt}) \geq 0, j = 1, 2, 3, 4, 5\}$

$= Pr\{ \delta_{it} \tau_{it} \leq \delta_{it} [|SD_{it}| - f(X_i, Z_{it}, \theta_{it})]\}$, and

$\phi_{ijt}\xi_{ijt} \leq \phi_{ijt} [TTS_{ijt} - g(X_i, Z_{ijt}, \theta_{ijt})], j = 1, 2, 3, 4, 5\}$ (4.36)

The likelihood of a sequence of decisions $[(\delta_{it}, \phi_{i1t}, \phi_{i2t}, \phi_{i3t}, \phi_{i4t}, \phi_{i5t}), t = 1, 2, \ldots, T]$ for individual i is thus given by:

$Pr[(\delta_{it}, \phi_{i1t}, \phi_{i2t}, \phi_{i3t}, \phi_{i4t}, \phi_{i5t}), t = 1, 2, \ldots, T]$

$= Pr\{ \delta_{it}\tau_{it} \leq \delta_{it} [|SD_{it}| - f(X_i, Z_{it}, \theta_{it})]$ and

$\phi_{i1t}\xi_{i1t} \leq \phi_{i1t} [TTS_{i1t} - g(X_i, Z_{i1t}, \theta_{i1t})]$ and

$\phi_{i2t}\xi_{i2t} \leq \phi_{i2t} [TTS_{i2t} - g(X_i, Z_{i2t}, \theta_{i2t})]$ and

$\phi_{i3t}\xi_{i3t} \leq \phi_{i3t} [TTS_{i3t} - g(X_i, Z_{i3t}, \theta_{i3t})]$ and

$\phi_{i4t}\xi_{i4t} \leq \phi_{i4t} [TTS_{i4t} - g(X_i, Z_{i4t}, \theta_{i4t})]$ and

$\phi_{i5t}\xi_{i5t} \leq \phi_{i5t} [TTS_{i5t} - g(X_i, Z_{i5t}, \theta_{i5t})], t = 1, 2, \ldots, T\}$ (4.37)

In this case, there are 6T+1 alternatives with respective "utilities":

Auxiliary alternative	$U_0 = 0$
Departure time, Day 1	$U_1 = \delta_{i1} [f(X_i, Z_{i1}, \theta_{i1}) - \|SD_{i1}\| + \tau_{i1}]$
Decision node 1, Day 1	$U_2 = \phi_{i11} [g(X_i, Z_{i11}, \theta_{i11}) - TTS_{i11} + \xi_{i11}]$
Decision node 2, Day 1	$U_3 = \phi_{i21} [g(X_i, Z_{i21}, \theta_{i21}) - TTS_{i21} + \xi_{i21}]$
Decision node 5, Day 1	$U_6 = \phi_{i51} [g(X_i, Z_{i51}, \theta_{i51}) - TTS_{i51} + \xi_{i51}]$
Departure time, Day 2	$U_7 = \delta_{i2} [f(X_i, Z_{i2}, \theta_{i2}) - \|SD_{i2}\| + \tau_{i2}]$
Decision node 1, Day 2	$U_8 = \phi_{i12} [g(X_i, Z_{i12}, \theta_{i12}) - TTS_{i12} + \xi_{i12}]$
Decision node 5, Day T	$U_{6T} = \phi_{i5T} [g(X_i, Z_{i5T}, \theta_{i5T}) - TTS_{i5T} + \xi_{i5T}]$ (4.38)

Therefore, the probability of a sequence of decisions for departure time and route choices over T days, Pr [(δ_{it} , ϕ_{i1t} ,ϕ_{i2t} , ϕ_{i3t} , ϕ_{i4t} , ϕ_{i5t}), where t = 1, 2, ... , T], is identical to the probability of selecting the auxiliary alternative, P_0:

$$P_0 = \text{Prob}\{\ \delta_{i1}\,[f(X_i, Z_{i1}, \theta_{i1}) - |SD_{i1}| + \tau_{i1}\,] < 0, \text{ and}$$

$$\phi_{i11}\,[g(X_i, Z_{i11}, \theta_{i11}) - TTS_{i11} + \xi_{i11}\,] < 0, \text{ and}$$

$$\phi_{i21}\,[g(X_i, Z_{i21}, \theta_{i21}) - TTS_{i21} + \xi_{i21}\,] < 0, \text{ and}$$

$$\phi_{i51}\,[g(X_i, Z_{i51}, \theta_{i51}) - TTS_{i51} + \xi_{i51}\,] < 0, \text{ and}$$

$$\delta_{i2}\,[f(X_i, Z_{i2}, \theta_{i2}) - |SD_{i2}| + \tau_{i2}\,] < 0, \text{ and}$$

$$\phi_{i12}\,[g(X_i, Z_{i12}, \theta_{i12}) - TTS_{i12} + \xi_{i12}\,] < 0, \text{ and}$$

$$\phi_{i5T}\,[g(X_i, Z_{i5T}, \theta_{i5T}) - TTS_{i5T} + \xi_{i5T}\,] < 0\ \} \qquad (4.39)$$

From equation (4.39), the above equation can be rewritten as follows.

$$P_0 = \text{Prob}\{\ \delta_{i1}\,[IBD_{i1} - |SD_{i1}\,|\,] < 0, \text{ and}$$

$$\phi_{i11}\,[IBR_{i11} - TTS_{i11}\,] < 0, \text{ and}$$

$$\phi_{i21}\,[IBR_{i21} - TTS_{i21}\,] < 0, \text{ and}$$

$$\phi_{i51}\,[IBR_{i51} - TTS_{i51}\,] < 0, \text{ and}$$

$$\delta_{i2}\,[IBD_{i2} - |SD_{i2}\,|\,] < 0, \text{ and}$$

$$\phi_{i12}\,[IBR_{i12} - TTS_{i12}\,] < 0, \text{ and}$$

$$\phi_{i5T}\ [IBR_{i5T} - TTS_{i5T}\,] < 0\ \} \qquad (4.40)$$

The U's are random variables with a multivariate normal distribution MVN (V, Σ_U). In deriving Σ_U, the error terms can be modelled as stand-alone alternative specific parameters and the variables τ_{it}, ξ_{ijt} can be omitted with no loss of generality. Therefore, the expression of indifference bands for departure time and route switching decisions can be rewritten as:

$$IBD_{it} = f'(X_i, Z_{it}, \theta_{it})$$

$$IBR_{ijt} = g'(X_i, Z_{ijt}, \theta_{ijt}) \qquad (4.41)$$

where $f'(X_i, Z_{ijt}, \theta_{ijt}) = \omega_{it} f'_e (X_i, Z_{it}, \theta_{it}) + (1-\omega_{it}) f'_l (X_i, Z_{it}, \theta_{it})$

$g'(X_i, Z_{ijt}, \theta_{ijt}) = W_{ijt} TTC_{ijt} g'_r(X_i, Z_{ijt}, \theta_{ijt}) + (1-W_{ijt}) g'_m(X_i, Z_{ijt}, \theta_{ijt})$

$f'_e (X_i, Z_{it}, \theta_{it}) = f_e (X_i, Z_{it}, \theta_{it}) + \tau_{it,e}$

$f'_l (X_i, Z_{it}, \theta_{it}) = f_l (X_i, Z_{it}, \theta_{it}) + \tau_{it,l}$

$g'_r(X_i, Z_{ijt}, \theta_{ijt}) = g_r (X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,r}$

$g'_m(X_i, Z_{ijt}, \theta_{ijt}) = g_m (X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,m}$

The utilities can also be rewritten as:

Auxiliary alternative	$U_0 = 0$	
Departure time, Day 1	$U_1 = \delta_{i1} [f'(X_i, Z_{i1}, \theta_{i1}) - \lvert SD_{i1} \rvert]$	
Decision node 1, Day 1	$U_2 = \phi_{i11} [g'(X_i, Z_{i11}, \theta_{i11}) - TTS_{i11}]$	
Decision node 2, Day 1	$U_3 = \phi_{i21} [g'(X_i, Z_{i21}, \theta_{i21}) - TTS_{i21}]$	
Decision node 5, Day 1	$U_6 = \phi_{i51} [g'(X_i, Z_{i51}, \theta_{i51}) - TTS_{i51}]$	
Departure time, Day 1	$U_7 = \delta_{i2} [f'(X_i, Z_{i2}, \theta_{i2}) - \lvert SD_{i2} \rvert]$	
Decision node 1, Day 2	$U_8 = \phi_{i12} [g'(X_i, Z_{i12}, \theta_{i12}) - TTS_{i12}]$	
Decision node 5, Day T	$U_{6T} = \phi_{i5T} [g'(X_i, Z_{i5T}, \theta_{i5T}) - TTS_{i5T}]$	(4.42)

SUMMARY

This chapter has presented the theoretical framework for modeling tripmaker travel decisions under real-time information, namely: the user compliance and satisfaction models for the event count (frequency of decisions) approach and the indifference switching bands for the bounded rationality approach.

Poisson regression models are proposed as an indirect approach that focuses on the frequency of compliance and satisfaction decisions and relate such decisions to the

characteristics of the information supplied, the performance of the traffic system, as well as the commuters' own. A detailed background review of the Poisson model as well as alternative models (negative binomial) is provided in this chapter, together with testing procedures for the appropriate use of Poisson and negative binomial models.

An indifference band model framework is also proposed in this chapter to investigate the mechanisms governing commuters' route and departure time switching decisions under the provision of real-time traffic information. The dynamic indifference band model can be formulated as a multinomial probit model framework that takes into account tripmakers' learning from past experiences with the system and explores the interaction effects between departure time choice, pre-trip and en-route route selections made by the same individual.

CHAPTER 5: ESTIMATION OF COMMUTER BEHAVIOR MODELS UNDER DIFFERENT REAL-TIME INFORMATION STRATEGIES

INTRODUCTION

The previous chapter has discussed the theoretical framework of two types of models employed here: (1) Poisson and negative binomial regression models of user compliance and satisfaction under real-time traffic information; and (2) multinomial probit models for tripmakers' day-to-day decisions to change route and/or departure time in response to real-time traffic information. Based on these modeling frameworks, the focus of this chapter is on the empirical realization and estimation of the travel behavior models under ATIS with varying information quality and credibility, using the data collected from a set of laboratory experiments as described in Chapter 3. These calibrated models of driver decision form the principal basis for articulating and testing the substantive hypotheses of this study.

This chapter is organized into six sections. The following section describes the general characteristics of the participants, as well as the exploratory analyses of: (1) route and departure time switching behavior revealed in the data; (2) information users' compliance decisions on route advice; and (3) commuters' overall satisfaction on departure time and route choices. The estimation results of the frequency model of user decisions to accept and comply with real-time route information using the observation data collected from this experiment are presented, followed by the estimation results of frequency model of commuters' decisions to not to change the departure time or the route (pre-trip or en-route) choices made from the preceding trip, as a measure of user satisfaction. Next, the model specifications and estimation results of joint departure time and route switching indifference bands models are discussed. Finally, a summary of the substantive behavioral conclusions derived from the estimation results is given.

EXPLORATORY ANALYSIS

General Characteristics

Prior to engaging in the interactive experiment, each participating subject was asked to complete a six-item questionnaire (see Appendix A) to provide responses to a set of questions, including age, gender, occupation, commuting frequency by drive per week, tolerance to late arrival at the workplace, and preferred arrival time at workplace. The general characteristics of the participants are summarized in Table 5.1. The majority of the subjects were between the ages of twenty to sixty (92.5%). The average actual travel time to work was 25.8, 26.8, and 26.1 minutes on days 2, 3, and 4, respectively. The work start time was set at 8:00 AM for all participants in the experiment. Based on the collected data, about 63.9% of the participants reported tolerance to lateness in excess of five minutes at the workplace and the average

preferred arrival time was 19.6 minutes before work start time for the participants. The preferred arrival time reflects a safety margin to protect against lateness at work and allows some time for preparation at the onset of the working day. It was found to be an important determinant of commuter behavior in previous day-to-day dynamics experiments (Mahmassani and Chang, 1985).

Participants were also asked to complete a post-experiment questionnaire, primarily in regard to their perceptions of the usefulness of real-time information systems. Based on these responses, more than half of the participants perceived the information they receive from the system only as reasonably accurate (63.2%). Most of the participants indicated their willingness to adopt such an information systems for future actual use (87.9% for pre-trip planning; 87.2% for obtaining en-route information).

TABLE 5.1: GENERAL CHARACTERISTICS OF THE PARTICIPANTS

Characteristics		
Number of Participants		124
Age	Under 20	0.0%
	20-39	29.3%
	40-59	63.2%
	Over 60	7.5%
Gender	Male	37.6%
	Female	62.4%
Average actual travel time to work	Day 2	25.8 min
	Day 3	26.8 min
	Day 4	26.1 min
Average preferred arrival time before work start		19.6 min
% with lateness tolerance (> 5 min) at work		63.9%
Perceived reliability of the information system	Extremely accurate	18.0%
	Reasonably accurate	63.2%
	Moderately accurate	18.0%
	Inaccurate	0.8%
	Extremely inaccurate	0.0%
Potential usage of the information system (pre-trip)	Definitely	38.3%
	Probably	49.6%
	Undecided	7.5%
	Probably not	3.8%
	Definitely not	0.8%
Potential usage of the information system (en-route)	Definitely	43.6%
	Probably	43.6%
	Undecided	6.0%
	Probably not	6.0%
	Definitely not	0.8%

Departure Time and Route Switching Decisions

Described below are the repetition and variability of tripmakers' departure time decisions and route choices both pre-trip and en-route in the experiment. In the analysis, only days 2, 3, and 4 are considered; day 1 was eliminated as a "trial" day, though it provided the basis for defining pre-trip route and/or departure time switches on day 2.

Pre-Trip and En-Route Route Decisions. Pre-trip route switching is defined relative to one's route on the preceding day. This day-to-day definition of switching considers the current day's route (pre-trip) to be a switch from the previous day if it differs from the previous day's initial (pre-trip) route. An en-route path switch occurs when the route chosen to the destination at the current decision point (excluding the pre-trip decision node) is different from the one chosen at the previous decision point (including the pre-trip decision node). The average route switching rate for both pre-trip and en-route on each commuting day is shown in Table 5.2. The average route switching rate decreases from day 2 to day 4, indicating that the commuters tend to stay on the same route when their commuting experiences accumulate. The overall percentage of route switching is 33.0% over the three commuting days in the experiment.

Route switch ratios were further calculated for each commuter by dividing the number of actual switches by the number of possible switches, for both pre-trip and en-route (a ratio of 1.0 indicates a switch at every possible decision opportunity). The cumulative distribution (across participants) of the route switching ratios is given in Figure 5.1. The results indicate that about 20 percent of the commuters never changed their en-route route selection in the experiment, while only around 2 percent of the commuters never switched path pre-trip.

TABLE 5.2: AVERAGE ROUTE SWITCHING RATE OF THE PARTICIPANTS AT EACH DECISION NODE

	Node 1	Node 2	Node 3	Node 4	Node 5	Average
	(Pre-trip)	(En-route)				(day)
Day 2	36.7%	35.2%	23.2%	28.4%	46.2%	33.9%
Day 3	31.8%	33.9%	28.4%	28.7%	49.2%	34.4%
Day 4	28.7%	31.2%	22.3%	25.1%	46.5%	30.8%
Average (node)	32.4%	33.4%	24.6%	27.4%	47.3%	33.0%

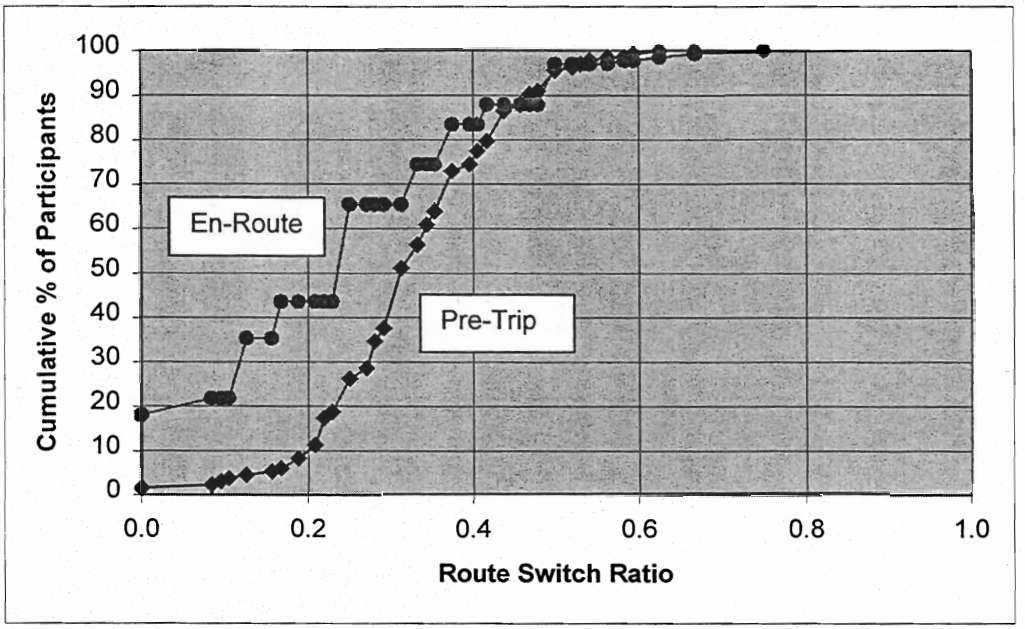


Figure 5.1: Cumulative distributions of route switching ratios for pre-trip and en-route

Departure Time Decisions. The day-to-day definition of switching given by Mahmassani and Jayakrishnan (1991) is used in this study to capture commuters' departure time switching behavior. By the day-to-day switching definition, the current day's departure time is considered a switch from the previous day if the absolute value of the difference between two consecutive days' departure times is greater than or equal to some minimum threshold (based on the results from Mahmassani and Liu (1997), a threshold of 5 minutes was selected in this study). The aggregate rate of departure time switching for the morning commute with work starting time controlled monotonically decreased over the 4-day period, as shown in Figure 5.2.

Departure time switching ratios were obtained by dividing the number of actual switches by the number of possible switches for each individual (a ratio of 1.0 indicates a switch at every possible decision opportunity). Figure 5.3 depicts the cumulative relative frequency distributions (across participants) of the departure time switching ratios. The percentage of participants who never changed their departure time was 48% over the 4-day period.

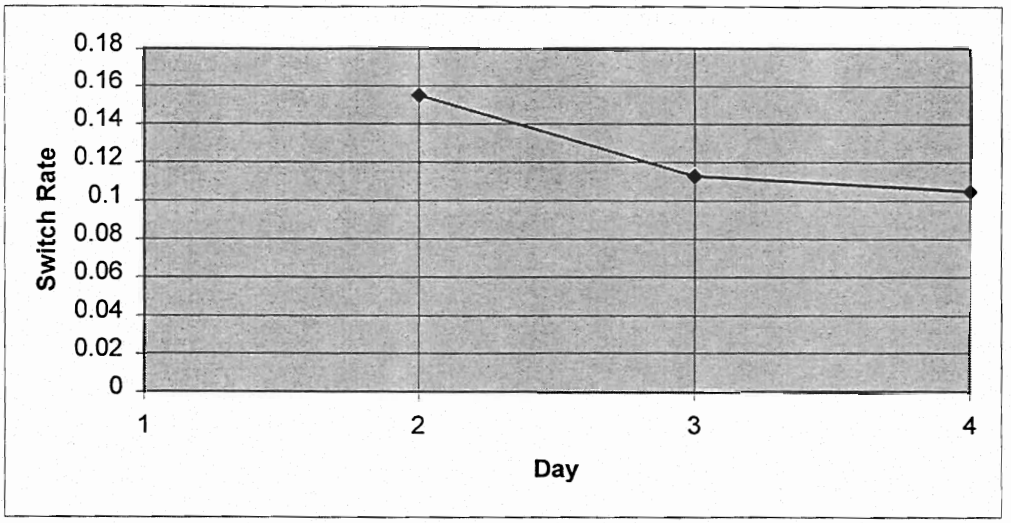


Figure 5.2: Daily departure time switch rate for the morning commute based on the day-to-day switching definition

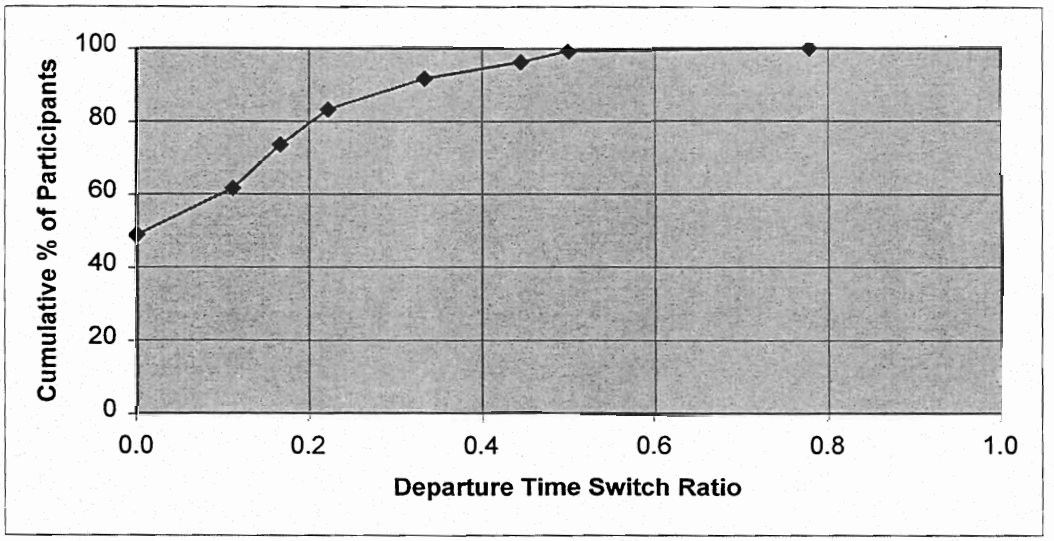


Figure 5.3: Cumulative distributions of departure time switch ratios for the morning commute in the second experiment based on the day-to-day switching definition

Compliance Decisions with Route-Based Information

This section describes the variability of tripmakers' compliance decisions to real-time route information, both pre-trip and en-route. In this analysis, only days 2, 3, and 4 are considered; day 1 was discarded as a "trial" day. Moreover, departure time choices are not included in this compliance framework since none of the information strategies in the experiment provide information to instruct commuters on the "best" time to depart for work.

ATIS users' compliance behavior can be captured by the observed frequency of commuter decisions to comply with or accept real-time traffic information. Strictly speaking, decisions of compliance or acceptance are applicable only under ATIS systems through which prescriptive or normative information, advice, and guidance are given to the commuters to be followed. This requirement has been relaxed to legitimize the descriptive information strategies in this experiment since they all provide the commuters trip time information on all of the available facilities, from which the "best" path can be inferred. Therefore, in the context of our experiment, both the prescriptive and the descriptive information are included in our compliance model.

The frequency of compliance decisions made by commuters per trip is shown in Table 5.3. The highest possible number of compliance decisions per trip for any commuter is five, consisting of one pre-trip route choice and four en-route path decisions. Departure time choices are not considered here because no trip time information were provided to the information users to explicitly instruct them to make departure time adjustments, even though the feedback mechanisms could give the commuters a basis to make such adjustments through experience gained from previous trips. As shown in the table, 42.0% of all route decisions per trip were compliant (100% compliance) with the information provided, while only 3.1% of those were completely non-compliant (0% compliance). The rest of the route decisions (54.9%) lie in between, ranging from 1 compliance decision (20% compliance) to 4 compliance decisions (80% compliance) per trip. The overall compliance rate for route choices in response to real-time information is 76.0%.

TABLE 5.3: FREQUENCY OF ROUTE COMPLIANCE DECISIONS PER TRIP

Compliance Decisions per trip (up to 5)	Frequency of trips
5	469 (42.0%)
4	206 (18.4%)
3	215 (19.3%)
2	119 (10.7%)
1	72 (6.5%)
0	35 (3.1%)
Total	1116 (100.0%)

It should be noted that a decision to comply with real-time information does not always constitute a route switch and vise versa. It depends on whether the path the commuter is currently on is the "best" path, as suggested by the real-time information. If his/her current path is indeed the " best" path, then the decision to remain on the current path complies with the

information received. Alternatively, by switching to the "best" path when the commuter's current path is not the "best" path, he/she has complied.

Satisfaction in Trip-Making Decisions

This section describes the repetition and variability of tripmakers' satisfaction behavior under real-time information. Included in this framework are pre-trip departure time and route choices as well as en-route path decisions. In this analysis, only days 2, 3, and 4 are considered; day 1 was discarded as a "trial" day, though it provided the basis for identifying departure time and route switches on day 2.

Under the proposed modeling framework, satisfaction can be captured by the observed frequency of trip-making decisions to not switch either departure time or route, pre-trip or en-route. A commuter may perceive over time, through his/her experience with the traffic system and the real-time information received, a satisfactory commuting route that consists of segments from different highways. Thus, a route switch under this framework is defined as a deviation from the route choice made from the previous day for that particular segment the commuter is traversing. The same definition for the departure time switches previously discussed is applied here. Table 5.4 shows the frequency of non-switches in the pre-trip departure time and route choices as well as en-route path decisions made from the previous day. Out of a total of 1116 trips recorded from the experiment, 339 trips (30.4%) exhibited total satisfaction under our satisfaction framework by selecting the same departure time and identical route from the preceding trip. Neither pre-trip nor en-route adjustments were made.

TABLE 5.4: FREQUENCY OF NON-SWITCHING DECISIONS
(AS A MEASURE OF SATISFACTION)

Non-Switching Decisions per trip (up to 6)	Frequency of trips
6	339 (30.4%)
5	213 (19.1%)
4	172 (15.4%)
3	183 (16.4%)
2	105 (9.4%)
1	65 (5.8%)
0	39 (3.5%)
Total	1116 (100.0%)

ESTIMATION RESULTS FOR COMPLIANCE MODELS

This section focuses on developing and calibrating user compliance models of commuters' pre-trip and en-route route decisions under ATIS information for morning commutes. Following

the modeling framework developed in Chapter 4, the models of the frequency of compliance decisions on route choice under real-time information can be calibrated using the data collected from the experiment. The first information user compliance model is calibrated to examine the relative differences in behavior under the three controlled experimental factors as listed below:

(1) Nature of information: prescriptive; descriptive.

(2) Information quality: predicted; prevailing; predicted perturbed; differential predicted; differential prevailing; random.

(3) Feedback: own trip experience; recommended; actual best.

A detailed description of these experimental factors can be found in Chapter 3.

A Poisson regression model is estimated for this purpose with these experimental factors represented in the model as binary indicators, as shown in Table 5.5. The results show that all variables are of plausible sign and, all but one, are highly statistically significant. Moreover, the log-likelihood movement from zero to convergence is quite satisfactory.

The first experimental factor consists of two levels, descriptive vs. prescriptive information. The resulting coefficient of the prescriptive information indicator reveals that commuters tend to comply more with the real-time information if it is prescriptive or normative, i.e., in the nature of advice, recommendation, or guidance, than if it is descriptive in nature.

TABLE 5.5: ESTIMATION RESULTS FOR POISSON REGRESSION MODEL OF ROUTE CHOICE COMPLIANCE FREQUENCYUNDER REAL-TIME INFORMATION ON CONTROLLED EXPERIMENTAL FACTORS

Explanatory Variable	Estimated Coefficient	t-Statistic
Constant	0.9120	12.66
NATURE OF INFORMATION		
Prescriptive Information	0.0818	2.19
INFORMATION QUALITY		
Predicted	0.3136	4.19
Prevailing	0.2918	3.91
Predicted Perturbed	0.2258	2.66
Differential Predicted	0.2020	2.21
Differential Prevailing	0.1553	1.30
FEEDBACK		
Actual Best	0.1317	3.02
Recommended	0.0955	2.10
Log-likelihood at zero	-2116.7	
Log-likelihood at convergence	-1121.9	
$\rho 2$	0.47	
Number of observations	1116	

For the second experimental factor, six levels are considered here, namely predicted information (most reliable), prevailing information (second most reliable), predicted perturbed information (somewhat less reliable), differential predicted information (more unreliable), differential prevailing information (even more unreliable), and random information (most unreliable). Thus, five binary indicators are incorporated into the model. The results show that all of the binary variables have the plausible sign, though with one of them not statistically significant above the 10% level. The results imply that there tends to exist a hierarchy of information quality under which different levels of compliance can be achieved. In this experiment, the more reliable the information, the higher is the rate of compliance. Under this hierarchy, commuters are inclined to comply most with predicted information, followed by prevailing information, then predicted perturbed information, differential predicted information, differential prevailing information, and least with random information.

Under the third experimental factor, participants in the experiment were provided at the end of each simulated trip with actual performance feedback *post facto*. Three levels of feedback were supplied as follows: (1) feedback on own experience; (2) feedback on recommended path by the system; and (3) feedback on the actual best path. Consequently, two binary indicators are incorporated into the model. The results show that all of the binary variables are found to have the plausible sign and are statistically significant. This highlights the importance of post-trip evaluation feedback in attaining high levels of compliance. The findings suggest that ATIS systems providing feedback with either recommended or actual best paths are likely to experience a higher rate of user compliance than systems with feedback on own experience only. The estimation results show that commuters receiving feedback with the actual best path tend to comply more than those receiving feedback with the path recommended by the system. Commuters with the knowledge of only their own trip performance tend to comply the least in the experiment.

Another Poisson regression model of the frequency of compliance decisions is estimated using the data collected from the experiment, relating to the following five main sets of "explanatory" components: (1) information quality, (2) experience, (3) information-switching interaction, (4) nature of information, and (5) post-trip feedback. The results are shown in Table 5.6. By considering these explanatory components in this model, more comprehensive and deeper insights to the underlying mechanisms of how users combine ATIS information with past experience and its influence on compliance behavior can be gained.

The first objective of calibrating this model of user compliance is to assess how and to what extent the quality of real-time information generally affects an ATIS commuter's decision to accept and comply with the route choice information supplied. Accuracy and reliability have often

been used to represent the effect of information quality. Unfortunately, both measures continue to be used interchangeably by several researchers leading to inconsistent terminology. In the interest of clarity, two separate measures are defined below to distinguish the two, even while recognizing the inter-relationship between them.

Accuracy is defined as representing the discrepancy between information reported by the ATIS and users' experience in the traffic system (for instance, the difference between reported and experience travel times). Of particular interest is the effect of over-estimation – when the reported travel time exceeds the experienced trip time, and under-estimation – when the reported information under-estimates the actual trip time. Two measures of accuracy are considered. Relative error is the ratio of deviation of reported to actual trip time with respect to actual trip time, as defined in the previous section. Absolute error is the difference between reported and actual trip times. It is found that, while both significantly influenced compliance, the relative error specification added much more explanatory power to the model in terms of log-likelihood than the absolute error specification. Only the relative error specification is included in the final model specification. Both over-estimation and under-estimation errors are found to significantly reduce the likelihood of compliance. Under-estimation errors have a greater negative effect than over-estimation errors on compliance as expected due to the possibility of late arrival.

The second measure of information quality considered is reliability. Following standard convention in probability, reliability is defined here as the probability that the accuracy exceeds a threshold. Reliability measures are calculated at each decision node for each user as the fraction of prior experiences with absolute value of relative error falling below a threshold. For instance, the reliability at a 10% threshold for relative error is calculated as number of previous experiences for the user where the absolute value of relative error was below 10%, divided by the total number of previous experiences. Using this definition, reliability variables are calculated for thresholds of 10, 20, 30, 40, and 50%. Increasing reliability of information is found to result in higher compliance. Nevertheless, none of these variables are statistically significant and consequently are not included in the final model specification.

Next, the role of experience on compliance behavior is examined. First the influence of recency and frequency of experiences is considered. There is substantial evidence from cognitive behavior literature indicating that recent events are subject to quicker and more accurate recall than events in the distant past. In order to test the effect of recent events, a dummy variable *traffic jam* representing whether a user was stuck in traffic on the segment immediately preceding the decision node, is included in the specification. Providing strong evidence of the effect of recent experience in traffic, this variable is significant and negative indicating a lower compliance following a bad experience.

TABLE 5.6: ESTIMATION RESULTS FOR POISSON REGRESSION MODEL OF ROUT CHOICE COMPLIANCE FREQUENCY UNDER REAL-TIME INFORMATION

Explanatory Variable	Estimated Coefficient	t-Statistic
Constant	1.6804	32.90
INFORMATION QUALITY		
Over Estimation Error	-0.0846	-1.34
Under Estimation Error	-0.1413	-3.89
EXPERIENCE		
Traffic Jam	-0.6226	-4.46
Early Schedule Delay	-0.0013	-1.53
Late Schedule Delay	-0.0035	-1.81
INFORMATION-SWITCHING INTERACTION		
Switching Cost	-0.8637	-13.04
Compliance Benefit	0.0503	1.43
NATURE OF INFORMATION		
Prescriptive Information	0.0543	1.46
FEEDBACK		
Actual Best	0.0914	2.12
Recommended	0.0603	1.36
Log-likelihood at zero	-2116.7	
Log-likelihood at convergence	-931.5	
$\rho 2$	0.56	
Number of observations	1116	

The second aspect of the effect of experience relates to how and to what extent schedule delay from the previous day affects how often commuters comply with route-based advice. Both early and late schedule delays have been included in the model. It is found that both the variables *early schedule delay* and *late schedule delay* are statistically significant. Both variables have negative coefficients indicating that commuters tend to comply less with the real-time information when they experience early or late schedule delays. The variable *late schedule delay* has a higher (more negative) value than that for the *early schedule delay* which shows that commuters tend to be even less compliant when experienced with schedule delay at the late side than when experienced with schedule delay at the early side. This confirms the findings from previous studies (Mahmassani and Liu, 1997) that the tolerable schedule delay is one of the most important criteria governing commuters' trip-making decisions and that commuters tend to switch more when faced with late schedule delay than with early schedule delay.

Following the estimation results of the frequency models, the role of information, behavior and supply interaction is investigated next, in the light of the association between compliance and switching behavior. It is found that the proxy switching cost is found to be a particularly strong variable. The coefficient indicates that commuters tend not to comply with real-time information when switching from their current routes is required. The farther distance the system suggests

that they divert, the less willing they are to accept and comply. The results validate the plausibility and reasonableness of operationalizing the bounded rationality framework to model commuter switching decisions under real-time traffic information. Under this framework, an indifference band of switching is rationalized and may be interpreted as a cost of switching similar to the findings here. On the flip side of the cost of complying, the benefit of complying is considered particularly when it involves switching. To reflect the benefits, the relative trip time saving (reported trip time saving by complying reported trip time on current path) that occurs by complying is included. It is found that the greater the benefits of complying, the higher the likelihood of compliance.

Finally, the nature of real-time information and post-trip feedback are included in the model as binary indicator variables. Prescriptive information is found to lead to greater compliance than descriptive information. Providing feedback on recommended path or best path (ex post) appears to build the credibility of the information system and is found to increase compliance than when feedback is provided only on own experience. The results are consistent with those from the previous model in Table 5.5.

The strict assumptions of Poisson models is tested next, following the approach described in Chapter 4. In this testing approach, the regression-based test proposed by Cameron and Trivedi (1986) is first conducted by estimating the significance of g(μ_i) in

$$H_o : \text{var}[\, y_i \,] = \mu_i$$

vs.

$$H_a : \text{var}[\, y_i \,] = \mu_i + \alpha * g(\mu_i)$$

There are two possibilities suggested for g(μ_i), μ_i or μ_i^2. Both of them are tested independently (estimated μ_i = -0.0045 with t-statistics = -0.14 and μ_i^2 = -0.0013 with t-statistics = -0.15) and the t-statistics are found to be less than 1.0. Therefore, according to this test proposed by Cameron an Trivedi, there is no evidence of over- or under-dispersion in the data collected from the experiment.

Next the negative binomial regression model is estimated. This is an extension of the Poisson regression model which allows the variance to differ from the mean. Following the approach discussed in Chapter 4, the variance of the process can be formulated as a function of the mean.

$$\text{var}(c_i) = E[c_i]\{1 + \alpha E[c_i]\}$$

The α is a measure of dispersion. The negative binomial is the correct choice of model and not the Poisson model if α is statistically significant. The results are shown in Table 5.7. α is found to be statistically very insignificant (t-statistics = 0.001), confirming Poisson is the

appropriate and correct model. Comparing the estimation results to those in Table 5.6 (Poisson model), it is found that while the parameter values are very close to one another, the respective significance is much lower in the negative binomial model.

ESTIMATION RESULTS FOR SATISFACTION MODELS

This section focuses on the development and estimation of models of tripmaker satisfaction under ATIS for morning work trips, as measured by the propensity to minimize changes in trip-making decisions over time. Both the pre-trip departure time and route decisions as well as en-route path choices are considered here under this satisfaction modeling framework. Under this framework, the overall satisfaction behavior can be gauged by the observed frequency of trip-making decisions in which drivers are satisfied with the current commuting conditions and do not wish to modify or switch either departure time or route, both pre-trip and en-route. It should be noted that route switching decisions here are defined as deviations from the route choice made from the previous day for that particular segment the commuter is traversing. A detailed description of this satisfaction framework can be found in Chapter 4.

The first information user satisfaction model is estimated to examine the relative differences in behavior under the three controlled experimental factors as listed below:

1) Nature of information: prescriptive; descriptive.
2) Information quality: predicted; prevailing; predicted perturbed; differential predicted; differential prevailing; random.
3) Feedback: own trip experience; recommended; actual best.

A detailed description of these experimental factors can be found in Chapter 3.

A Poisson regression model is estimated for this purpose with these experimental factors represented in the model as binary indicators, as shown in Table 5.8. The results show that all variables are of plausible sign and, all but one, are highly statistically significant. Moreover, the log-likelihood movement from zero to convergence is quite satisfactory.

The first experimental factor consists of two levels, descriptive vs. prescriptive information. The resulting coefficient of the prescriptive information indicator reveals that commuters tend to be more satisfied with the real-time information if it is prescriptive or normative than if it is descriptive. Of course, being more satisfied under the context of our modeling framework simply means the commuter made a lower number of adjustments in trip-making decisions than from the preceding trip.

TABLE 5.7: ESTIMATION RESULTS FOR NEGATIVE BINOMIAL REGRESSION MODEL OF ROUTE CHOICE COMPLIANCEFREQUENCY UNDER REAL-TIME INFORMATION

Explanatory Variable	Estimated Coefficient	t-Statistic
Constant	1.6809	17.19
INFORMATION QUALITY		
Over Estimation Error	-0.0848	-0.74
Under Estimation Error	-0.1412	-2.44
EXPERIENCE		
Traffic Jam	-0.6226	-2.95
Early Schedule Delay	-0.0013	-1.14
Late Schedule Delay	-0.0035	-0.91
INFORMATION-SWITCHING INTERACTION		
Switching Cost	-0.8640	-8.69
Compliance Benefit	0.0506	0.97
NATURE OF INFORMATION		
Prescriptive Information	0.0544	0.73
FEEDBACK		
Actual Best	0.0909	1.17
Recommended	0.0600	0.72
DISPERSION		
α	0.00002	0.001
Log-likelihood at zero	-2116.7	
Log-likelihood at convergence	-1197.2	
$\rho 2$	0.43	
Number of observations	1116	

TABLE 5.8: ESTIMATION RESULTS FOR POISSON REGRESSION MODEL OF FREQUENCY OF USER "SATISFACTION" UNDER REAL-TIME INFORMATION ON CONTROLLED EXPERIMENTAL FACTORS

Explanatory Variable	Estimated Coefficient	t-Statistic
Constant	1.3349	22.77
NATURE OF INFORMATION		
Prescriptive Information	0.1014	3.08
INFORMATION QUALITY		
Predicted	0.1784	2.41
Prevailing	0.1724	2.50
Predicted Perturbed	0.1175	1.92
Differential Predicted	0.1033	1.68
Differential Prevailing	0.0805	1.12
FEEDBACK		
Actual Best	0.1416	3.79
Recommended	0.1155	2.95
Log-likelihood at zero	-2184.2	
Log-likelihood at convergence	-1288.7	
$\rho 2$	0.41	
Number of observations	1116	

The second experimental factor consists of six levels, namely predicted information (most reliable), prevailing information (second most reliable), predicted perturbed information (somewhat less reliable), differential predicted information (more unreliable), differential prevailing information (even more unreliable), and random information (most unreliable). Thus, five binary indicators are incorporated into the model. The results show that all of the binary variables have the plausible sign and, all but one, are statistically significant above the 10% level. The results imply that there tends to exist a hierarchy of information quality under which different levels of satisfaction can be achieved. In our experiment, the more reliable the information is, the less switches are observed. Under this hierarchy, commuters are most inclined to be content with predicted information, followed by prevailing information, then predicted perturbed information, differential predicted information, differential prevailing information, and least with random information.

Under the third experimental factor design, participants in the experiment were provided at the end of each simulated trip with actual performance feedback *post facto*. Three levels of feedback were supplied as follows: (1) feedback on own experience; (2) feedback on recommended path by the system; and (3) feedback on the actual best path. Thus, two binary indicator variables are incorporated into the model. The results show that all the have the plausible sign and are statistically significant. These results highlight the importance of post-trip evaluation feedback in the design and implementation of a favorable ATIS system in attaining desirable levels of satisfaction consistent with ATIS system users' prior beliefs and expectations. ATIS systems providing feedback with either the recommended or actual best paths are inclined to acquire a higher level of user satisfaction than systems with feedback on own experience. The model shows that commuters receiving feedback with the actual best path tend to be less satisfied than those receiving feedback with the path recommended by the system. Commuters with the knowledge of only their own trip performance tend to be the least satisfied in the experiment.

Another Poisson regression model of the frequency of satisfaction decisions is estimated using the data collected from the experiment, relating to the following five main sets of "explanatory" components: (1) information quality, (2) experience, (3) dynamic component of trip-making decision convergence from day to day, (4) nature of information, and (5) post-trip feedback. The results are shown in Table 5.9.

TABLE 5.9: ESTIMATION RESULTS FOR POISSON REGRESSION MODEL OF FREQUENCY OF USER "SATISFACTION" DECISIONS UNDER REAL-TIME INFORMATION

Explanatory Variable	Estimated Coefficient	t-Statistic
Constant	1.4367	34.41
INFORMATION QUALITY		
Over Estimation Error	-0.0934	-1.70
Under Estimation Error	-0.1020	-2.07
EXPERIENCE		
Traffic Jam	-0.1319	-1.66
Standard Deviation of Previous Trip Times	-0.0044	-1.64
CONVERGENCE		
Day	0.1102	3.59
NATURE OF INFORMATION		
Prescriptive Information	0.0323	1.92
FEEDBACK		
Actual Best	0.1416	3.82
Recommended	0.1179	3.10
Log-likelihood at zero	-2184.2	
Log-likelihood at convergence	-1070.3	
$\rho 2$	0.51	
Number of observations	1116	

The first objective in estimating these user satisfaction models is to determine how and to what extent the quality of information affects how often commuters are satisfied with the current commuting conditions and do not wish to change trip-making decisions from the preceding trip. Based on the results of Mahmassani and Liu (1997), the quality of information was found to be a critical factor in governing commuters' day-to-day pre-trip and en-route travel decisions under real-time information. Following their results, the reliability of information as experienced by the commuters is captured by the independent variables *over-estimated error* and *under-estimated error*. The *over-estimated error* is defined as the relative difference between the actual travel time and the estimated travel time when the estimated travel time by the traffic information system exceeds the actual travel time. Conversely, the *under-estimated error* is the relative difference between the actual travel time and the estimated travel time when the actual travel time exceeds the estimated travel time by the traffic information system. Both over-estimation and under-estimation errors are found to significantly reduce the likelihood of user satisfaction. Under-estimation errors have a greater negative effect than over-estimation errors.

The second objective is to verify the existence of an increasing trend in non-switching behavior over time through which tripmakers exhibit diminishing propensity to make decisions to switch either departure time or route under real-time information. This is an especially desirable behavioral trend during the early stages of ATIS introduction. A variable containing the specific

day or trip number for the set of data collected is created for this purpose. This variable, simply named *day*, is used as an explanatory variable to test the presence and significance of this trend. If its estimated coefficient is statistically significant and has a positive value, then commuters have the inclination to converge in their trip-making decisions over time as a trend of increasing satisfaction. On the other hand, a negative coefficient would imply commuters' trip-making decisions tend to change more frequently from day-to-day and this would be a trend of decreasing satisfaction. The estimated coefficient of the variable *day* is found to be positive and statistically significant. This finding suggests that there exists a trend of diminishing propensity to switch under ATIS over time, that users of real-time information tend to become more content with their trip-making decisions over time, and that there may be a pattern of convergence in commuters' departure time and path choices under ATIS over time. This is a particularly encouraging finding as the implications to the successful deployment of ATIS technologies are enormous.

Next, the role of experience on compliance behavior is examined. First the influence of recency and frequency of experiences is considered. In order to test the effect of recent events, a dummy variable *traffic jam* representing whether a user was stuck in traffic on the segment immediately preceding the decision node, is included in the specification. Providing strong evidence of the effect of recent experience in traffic, this variable is significant and negative indicating a lower level of satisfaction following a bad experience.

The second aspect of the effect of experience relates to the extent the variability in trip times experienced by the commuter (represented by the standard deviation of trip times experienced on previous trips) affects how often commuters are satisfied with the current commuting conditions and do not wish to change trip-making decisions from the preceding trip. It is found that the higher the variability in trip time experienced, the lower level of user satisfaction is achieved.

Finally, the nature of real-time information and post-trip feedback are included in the model as binary indicator variables. Prescriptive information is found to lead to higher level of satisfaction than descriptive information. Providing feedback on recommended path or best path (ex post) appears to build the credibility of the information system and is found to increase satisfaction than when feedback is provided only on own experience. The results are consistent with those from the previous model in Table 5.8.

The assumptions of Poisson models is tested next, following the approach described in Chapter 4. In this testing approach, the regression-based test proposed by Cameron an Trivedi (1986) is conducted first by estimating the significance of g(μ_i) in

$$H_o : \text{var}[\, y_i \,] = \mu_i$$

vs. H_a : var[y_i] = μ_i + α*g(μ_i)

There are two possibilities suggested for g(μ_i), μ_i or μ_i^2. Both of them are tested independently (estimated μ_i = -0.0066 with t-statistics = -0.33 and μ_i^2 = -0.0049 with t-statistics = -0.37) and the t-statistics are found to be less than 1.0. Therefore, there is no evidence of over- or under-dispersion in the data collected from the experiment.

Next the negative binomial regression model is estimated. This is an extension of the Poisson regression model which allows the variance to differ from the mean. The variance of the process can be formulated as a function of the mean.

var(c_i) = E[c_i]{1 + α E[c_i]}

The α is a measure of dispersion. The negative binomial is the correct choice of model and not the Poisson model if α is significant. The results are shown in Table 5.10. α is found to be statistically insignificant (t-statistics < 0.001), confirming Poisson is the appropriate and correct model. Comparing the estimation results to those in Table 5.9 (Poisson model), it is found that while the parameter values are very close to one another, the respective t-statistics are much lower in the negative binomial model.

ESTIMATION RESULTS FOR JOINT DEPARTURE TIME AND ROUTE SWITCHING MODELS

This section focuses on calibrating the day-to-day dynamic models of commuter pre-trip departure time and route choices as well as en-route path switching decisions for morning commutes under different real-time information designs of varying degree of information quality and credibility. Based on the results of Mahmassani and Liu (1997), the best joint departure time and route switching indifference b and model is adopted here and estimated using the data collected from the experiment. A description of this underlying behavioral modeling framework is included in Chapter 4. The main purpose here is to investigate how and to what extent information systems with varying levels of information quality and credibility affect the travel behavior of commuters under this framework of joint departure time and route switching decisions.

The joint departure time and route switching indifference band model utilizes the mechanism under which departure time switching follows the tolerable schedule delay mechanism and trip time saving governs pre-trip route and en-route path switching decisions in response to real-time information. The basic specification of this departure time and route switching indifference band model consists of the following components: (1) initial band, (2) user characteristics component, (3) information reliability component, (4) myopic component, (5) schedule delay component,

incorporating individual preference, and (6) unobserved component. In addition, controlled experimental factors are incorporated as binary indicator variables in the first component of the model, as follows:

(1) Nature of information: prescriptive; descriptive.

(2) Information quality (trip time information based on): reliable prediction; prevailing condition; perturbed prediction; random.

(3) Feedback: own trip experience; recommended; actual best.

TABLE 5.10: ESTIMATION RESULTS FOR NEGATIVE BINOMIAL REGRESSION MODEL OF FREQUENCY OF USER "SATISFACTION" DECISIONS UNDER REAL-TIME INFORMATION

Explanatory Variable	Estimated Coefficient	t-Statistic
Constant	1.4369	24.64
INFORMATION QUALITY		
Over Estimation Error	-0.0938	-1.13
Under Estimation Error	-0.1022	-1.25
EXPERIENCE		
Traffic Jam	-0.1323	-1.21
Standard Deviation of Previous Trip Times	-0.0043	-1.08
CONVERGENCE		
Day	0.1104	2.05
NATURE OF INFORMATION		
Prescriptive Information	0.0322	1.19
FEEDBACK		
Actual Best	0.1414	2.62
Recommended	0.1176	2.12
DISPERSION		
α	0.000003	< 0.001
Log-likelihood at zero	-2184.2	
Log-likelihood at convergence	-1288.4	
$\rho 2$	0.41	
Number of observations	1116	

A detailed discussion of these factors of experimental design can be found in Chapter 3. It should be noted that both the differential predicted information and the differential prevailing information strategies are outside the scope of this joint switching framework, and thus, are not considered in this model. The general approach here is to calibrate three models of joint departure and route switching decisions, one for each experimental factor. Within each joint decision model is a set of binary indicator variables of initial indifference bands, each pertaining to a treatment level. These specifications of initial bands will be tested for their relative contribution

and significance to the observed switching decisions of commuters. The following three models have been specified and calibrated, each associated with one experimental factor.

Model 1: Nature of information

The specification of the indifference band of tolerable schedule delay for departure time switching decisions can be expressed as shown in equation (5.1). The specifications of the relative indifference band and the minimum trip time saving for route switching model can be expressed as shown in equations (5.2) and (5.3). The definitions of the terms included in these expressions are summarized in Table 5.11.

Departure Time Decision

$$
\begin{aligned}
IBD_{it} &= \omega_{it}\, c_1 + (1-\omega_{it})\, c_2 && \text{Initial Band}\\
&+ \omega_{it}\, c_{13}\, PRESCR_i + (1-\omega_{it})\, c_{14}\, PRESCR_i && \text{Experimental Factor Component}\\
&+ \omega_{it}\, c_3\, AGE_i + (1-\omega_{it})\, c_4\, AGE_i &&\\
&+ \omega_{it}\, c_5\, GENDER_i + (1-\omega_{it})\, c_6\, GENDER_i && \text{User Characteristic Component}\\
&+ \omega_{it}\, c_7\, SERRO_{it} + (1-\omega_{it})\, c_8\, SERRO_{it} &&\\
&+ \omega_{it}\, c_9\, SERRU_{it} + (1-\omega_{it})\, c_{10}\, SERRU_{it} && \text{Information Quality Component}\\
&+ \omega_{it}\, c_{11}\, \lambda_{it}\, (\Delta TR_{it} / \Delta DT_{it}) &&\\
&+ (1-\omega_{it})\, c_{12}\, \lambda_{it}\, (\Delta TR_{it} / \Delta DT_{it}) && \text{Myopic Component}\\
&+ \tau_{it} && \text{Unobserved Component} \quad (5.1)
\end{aligned}
$$

Route Decision (Including Pre-Trip and En-Route)

$$IBR_{ijt} = \max\,[\,\eta_{ijt} TTC_{ijt},\ \pi_{ijt}\,] \qquad j = 1, 2, 3, 4, 5$$

$$
\begin{aligned}
\eta_{ijt} &= \kappa_1\, a_1 + (1-\kappa_1)\, a_2 && \text{Initial Band}\\
&+ \kappa_1\, a_8\, PRESCR_i + (1-\kappa_1)\, a_9\, PRESCR_i && \text{Experimental Factor Component}\\
&+ a_3\, GENDER_i && \text{User Characteristics Component}\\
&+ a_4\, ERRO_{ijt} + a_5\, ERRU_{ijt} && \text{Information Quality Component}\\
&+ a_6\, SDPE_{ijt} + a_7\, SDPL_{ijt} && \text{Schedule Delay Component}\\
&+ \xi_{ijt,r} && \text{Unobserved Component} \quad (5.2)\\
\pi_{ijt} &= \kappa_1\, b_1 + (1-\kappa_1)\, b_2 && \text{Initial Band}\\
&+ \kappa_1\, b_8\, PRESCR_i + (1-\kappa_1)\, b_9\, PRESCR_i && \text{Experimental Factor Component}\\
&+ b_3\, GENDER_i && \text{User Characteristics Component}\\
&+ b_4\, ERRO_{ijt} + b_5\, ERRU_{ijt} && \text{Information Quality Component}\\
&+ b_6\, SDPE_{ijt} + b_7\, SDPL_{ijt} && \text{Schedule Delay Component}\\
&+ \xi_{ijt,m} && \text{Unobserved Component} \quad (5.3)
\end{aligned}
$$

TABLE 5.11: VARIABLE DEFINITIONS FOR THE INDIFFERENCE BAND IN JOINT DEPARTURE TIME AND ROUTESWITCHING MODEL

Element	Definition
AGE_i	Age of commuter i; 1, if age < 20; 2, if age $\in$ [20,39]; 3, if age $\in$ [40,59]; 4, if age > 60.
$GENDER_i$	Gender of commuter i; = 1, if male; = 0, if female.
$ERRO_{ijt}$	Over-estimation error provided by real-time information; the relative error between actual travel time and travel time reported from the system when actual travel time is shorter than reported travel time.
$ERRU_{ijt}$	Under-estimation error provided by real-time information; the relative error between actual travel time and travel time reported from the system when actual travel time is longer than reported travel time.
$SERRO_{it}$	Sum of the values of over-estimation error provided by real-time information including pre-trip and en-route on day t-1. $SERRO_{it} = (ERRO_{i2,t-1} + ERRO_{i3,t-1} + ... + ERRO_{i6,t-1})$ $ERRO_{i6,t-1}$: relative over-estimation error from node 5 to the destination in day (t-1)
$SERRU_{it}$	Sum of the values of under-estimation error provided by real-time information including pre-trip and en-route on day t-1. $SERRU_{it} = (ERRU_{i2,t-1} + ERRU_{i3,t-1} + ... + ERRU_{i6,t-1})$ $ERRU_{i6,t-1}$: relative under-estimation error from node 5 to the destination in day (t-1)
$\lambda_{t\tau}$	A binary indicator variable, equal to 0 if $DT_{it} = DT_{it-1}$; = 1, otherwise.
ΔTR_{it}	The difference between travel times of commuter i on day t and t-1 (minutes).
ΔDT_{it}	The amount of departure time that commuter i has adjusted between day t and t-1 (minutes).
$\omega_{t\tau}$	A binary indicator variable, equal to 1 if $SD_{it} > 0$ (early-side), or = 0, if $SD_{it} < 0$ (late-side)
Element	Definition
κ_1	A binary indicator variable, equal to 1 if j = 1 (pre-trip route decision), or = 0 if j = 2, 3, 4, 5 (en-route path decision)

TABLE 5.11 (CONT'D): VARIABLE DEFINITIONS FOR THE INDIFFERENCE BAND IN JOINT DEPARTURE TIME AND ROUTESWITCHING MODEL

$SDPE_{ijt}$	Early-side schedule delay relative to commuter's preferred arrival time for commuter i at decision node j on day t (minutes). $SDPE_{ijt} = \max\{PAT_i - RAT_{ijt}, 0\}$ PAT_i : preferred arrival time for commuter i RAT_{ijt} : predicted arrival time for commuter i from node j to destination according to the travel time provided by the real-time information system ($RAT_{ijt} = CLOCK_{ijt} + TTC_{ijt}$) $CLOCK_{ijt}$: current clock time for commuter i at node j on day t TTC_{ijt} : the trip time along the current path from decision node j to the destination for commuter i on day t
$SDPL_{ijt}$	Late-side schedule delay relative to commuter's preferred arrival time for commuter i at decision node j on day t (minutes). $SDPL_{ijt} = \max\{RAT_{ijt} - PAT_i, 0\}$
PRESCR	An alternative-specific variable, equal to 1 if prescriptive information; 0 if descriptive information.
PREDIC	An alternative-specific variable, equal to 1 if predicted information; 0 otherwise.
RANDOM	An alternative-specific variable, equal to 1 if random information; 0 otherwise.
Element	Definition
PERTUR	An alternative-specific variable, equal to 1 if perturbed information; 0 otherwise.
RECOMM	An alternative-specific variable, equal to 1 if feedback on recommended path information; 0 otherwise.
BEST	An alternative-specific variable, equal to 1 if feedback on actual best path; 0 otherwise.
a's, b's, c's, d's	parameters to be estimated
Element	Definition
$\tau_{i\tau}$	error term of departure time switching indifference band for commuter i on day t
$\xi_{i\varphi\tau,\rho}$, $\xi_{i\varphi\tau,m}$	error term of route switching indifference band for commuter i at node j on day t ($\eta_{i\varphi\tau}$, $\pi_{i\varphi\tau}$)

Model 2: Information Quality

The specification of the indifference band of tolerable schedule delay for departure time switching decisions can be expressed as shown in equation (5.4). The specifications of the relative indifference band and the minimum trip time saving for route switching model can be expressed as shown in equations (5.5) and (5.6).

Departure Time Decision

$$
\begin{aligned}
IBD_{it} &= \omega_{it}\, c_1 + (1-\omega_{it})\, c_2 && \text{Initial Band}\\
&+ \omega_{it}\, c_{13}\, PREDIC_i + (1-\omega_{it})\, c_{14}\, PREDIC_i &&\\
&+ \omega_{it}\, c_{15}\, RANDOM_i + (1-\omega_{it})\, c_{16}\, RANDOM_i &&\\
&+ \omega_{it}\, c_{17}\, PERTUR_i + (1-\omega_{it})\, c_{18}\, PERTUR_i && \text{Experimental Factor Component}\\
&+ \omega_{it}\, c_3\, AGE_i + (1-\omega_{it})\, c_4\, AGE_i &&\\
&+ \omega_{it}\, c_5\, GENDER_i + (1-\omega_{it})\, c_6\, GENDER_i && \text{User Characteristic Component}\\
&+ \omega_{it}\, c_7\, SERRO_{it} + (1-\omega_{it})\, c_8\, SERRO_{it} &&\\
&+ \omega_{it}\, c_9\, SERRU_{it} + (1-\omega_{it})\, c_{10}\, SERRU_{it} && \text{Information Quality Component}\\
&+ \omega_{it}\, c_{11}\, \lambda_{it}\, (\Delta TR_{it} / \Delta DT_{it}) &&\\
&+ (1-\omega_{it})\, c_{12}\, \lambda_{it}\, (\Delta TR_{it} / \Delta DT_{it}) && \text{Myopic Component}\\
&+ \tau_{it} && \text{Unobserved Component} \quad (5.4)
\end{aligned}
$$

Route Decision (Including Pre-Trip and En-Route)

$$IBR_{ijt} = \max\left[\, \eta_{ijt} TTC_{ijt},\ \pi_{ijt} \,\right] \qquad j = 1, 2, 3, 4, 5$$

$$
\begin{aligned}
\eta_{ijt} &= \kappa_1\, a_1 + (1-\kappa_1)\, a_2 && \text{Initial Band}\\
&+ \kappa_1\, a_8\, PREDIC_i + (1-\kappa_1)\, a_9\, PREDIC_i &&\\
&+ \kappa_1\, a_{10}\, RANDOM_i + (1-\kappa_1)\, a_{11}\, RANDOM_i &&\\
&+ \kappa_1\, a_{12}\, PERTUR_i + (1-\kappa_1)\, a_{13}\, PERTUR_i && \text{Experimental Factor Component}\\
&+ a_3\, GENDER_i && \text{User Characteristics Component}\\
&+ a_4\, ERRO_{ijt} + a_5\, ERRU_{ijt} && \text{Information Quality Component}\\
&+ a_6\, SDPE_{ijt} + a_7\, SDPL_{ijt} && \text{Schedule Delay Component}\\
&+ \xi_{ijt,r} && \text{Unobserved Component} \quad (5.5)
\end{aligned}
$$

$$
\begin{aligned}
\pi_{ijt} &= \kappa_1\, b_1 + (1-\kappa_1)\, b_2 && \text{Initial Band}\\
&+ \kappa_1\, b_8\, PREDIC_i + (1-\kappa_1)\, b_9\, PREDIC_i &&\\
&+ \kappa_1\, b_{10}\, RANDOM_i + (1-\kappa_1)\, b_{11}\, RANDOM_i &&\\
&+ \kappa_1\, b_{12}\, PERTUR_i + (1-\kappa_1)\, b_{13}\, PERTUR_i && \text{Experimental Factor Component}\\
&+ b_3\, GENDER_i && \text{User Characteristics Component}\\
&+ b_4\, ERRO_{ijt} + b_5\, ERRU_{ijt} && \text{Information Quality Component}
\end{aligned}
$$

$+ \; b_6 \, SDPE_{ijt} + b_7 \, SDPL_{ijt}$ Schedule Delay Component

$+ \; \xi_{ijt,m}$ Unobserved Component (5.6)

Model 3: Feedback

The specification of the indifference band of tolerable schedule delay for departure time switching decisions can be expressed as shown in equation (5.7). The specifications of the relative indifference band and the minimum trip time saving for route switching model can be expressed as shown in equations (5.8) and (5.9).

Departure Time Decision

$IBD_{it} = \omega_{it} \, c_1 + (1- \omega_{it}) \, c_2$ Initial Band

$+ \; \omega_{it} \, c_{13} \, RECOMM_i + (1- \omega_{it}) \, c_{14} \, RECOMM_i$

$+ \; \omega_{it} \, c_{15} \, BEST_i + (1- \omega_{it}) \, c_{16} \, BEST_i$ Experimental Factor Component

$+ \; \omega_{it} \, c_3 \, AGE_i + (1- \omega_{it}) \, c_4 \, AGE_i$

$+ \; \omega_{it} \, c_5 \, GENDER_i + (1- \omega_{it}) \, c_6 \, GENDER_i$ User Characteristic Component

$+ \; \omega_{it} \, c_7 \, SERRO_{it} + (1- \omega_{it}) \, c_8 \, SERRO_{it}$

$+ \; \omega_{it} \, c_9 \, SERRU_{it} + (1- \omega_{it}) \, c_{10} \, SERRU_{it}$ Information Quality Component

$+ \; \omega_{it} \, c_{11} \, \lambda_{it} \, (\Delta TR_{it} / \Delta DT_{it})$

$+ \; (1- \omega_{it}) \, c_{12} \, \lambda_{it} \, (\Delta TR_{it} / \Delta DT_{it})$ Myopic Component

$+ \; \tau_{it}$ Unobserved Component (5.7)

Route Decision (Including Pre-Trip and En-Route)

$IBR_{ijt} = \max [\eta_{ijt} TTC_{ijt}, \; \pi_{ijt}]$ j = 1, 2, 3, 4, 5

$\eta_{ijt} = \kappa_1 \, a_1 + (1-\kappa_1) \, a_2$ Initial Band

$+ \; \kappa_1 \, a_8 \, RECOMM_i + (1-\kappa_1) \, a_9 \, RECOMM_i$

$+ \; \kappa_1 \, a_{10} \, BEST_i + (1-\kappa_1) \, a_{11} \, BEST_i$ Experimental Factor Component

$+ \; a_3 \, GENDER_i$ User Characteristics Component

$+ \; a_4 \, ERRO_{ijt} + a_5 \, ERRU_{ijt}$ Information Quality Component

$+ \; a_6 \, SDPE_{ijt} + a_7 \, SDPL_{ijt}$ Schedule Delay Component

$+ \; \xi_{ijt,r}$ Unobserved Component (5.8)

$\pi_{ijt} = \kappa_1 \, b_1 + (1-\kappa_1) \, b_2$ Initial Band

$+ \; \kappa_1 \, b_8 \, PREDIC_i + (1-\kappa_1) \, b_9 \, PREDIC_i$

$$+ \kappa_1 b_{10} RANDOM_i + (1-\kappa_1) b_{11} RANDOM_i$$

$$+ \kappa_1 b_{12} PERTUR_i + (1-\kappa_1) b_{13} PERTUR_i \quad \text{Experimental Factor Component}$$

$$+ b_3 GENDER_i \quad \text{User Characteristics Component}$$

$$+ b_4 ERRO_{ijt} + b_5 ERRU_{ijt} \quad \text{Information Quality Component}$$

$$+ b_6 SDPE_{ijt} + b_7 SDPL_{ijt} \quad \text{Schedule Delay Component}$$

$$+ \xi_{ijt,m} \quad \text{Unobserved Component} \quad (5.9)$$

The following assumptions are embedded in the above model specifications. First, the initial bands governing pre-trip route switching decisions may be different from those for en-route path switching. Second, the age of commuters may affect their departure time switching behavior. Older commuters may tend to tolerate greater schedule delay than younger ones. Third, commuters' gender may influence their pre-trip departure time and route switching decisions. Female commuters may, on average, have a wider indifference band than males. Fourth, the reliability of real-time information may directly influence commuters' travel decisions including departure time and route switching. Fifth, for the departure time switching decision, commuters may tolerate a wider indifference band, given that a small adjustment could result in a relatively large difference in travel time. This effect can be captured by $\Delta TR_{it}/\Delta DT_{it}$ (Mahmassani and Chang, 1986). Sixth, the schedule delay relative to users' preferred arrival time may affect their pre-trip route and en-route path switching behavior under the provision of real-time information.

The error structure assumes no serial correlation for the relative indifference band and general correlation pattern for the minimum trip time saving for route switching model. The contemporaneous correlation effects between departure time and en-route path decisions are found to be not significant, and they are ignored. Therefore, the corresponding covariance terms between departure time and en-route path decisions are assumed to be zero in this analysis. A summary of the error structure for this joint switching indifference band can be found in Appendix C.

The estimation results of Model 1 for three consecutive days are presented in Table 5.12. The parameters that capture the effects of user characteristics for the departure time switching decisions are c3 through c6. The estimated values have correct signs and reasonable magnitudes. The estimates yield positive signs for c3 and c4, suggesting that older commuters tend to tolerate greater schedule delay than younger ones for departure time switching decision. The estimates yield negative signs for c5 and c6, revealing that male commuters have narrower

indifference band (i.e., are more likely to switch) than females for the departure time switching decision.

TABLE 5.12: THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 1)

Component / Attribute	Param.	Estimates	t
Initial tolerable schedule delay for DT (e) (descriptive information)	c1	12.0967	4.85
Initial tolerable schedule delay for DT (l) (descriptive information)	c2	7.0967	5.35
DT user characteristics 1 / AGE (e)	c3	4.9986	7.53
DT user characteristics 1 / AGE (l)	c4	2.7432	10.19
DT user characteristics 2 / GENDER (e)	c5	-2.4178	-10.96
DT user characteristics 2 / GENDER (l)	c6	-0.3067	-5.42
DT information reliability 1 / SERRO (e)	c7	4.0334	6.23
DT information reliability 1 / SERRO (l)	c8	0.0060	2.46
DT information reliability 2 / SERRU (e)	c9	1.6154	7.46
DT information reliability 2 / SERRU (l)	c10	0.7771	6.77
DT myopic / λ_{it} (ΔTR_{it} / ΔDT_{it}) (e)	c11	3.8697	5.64
DT myopic / λ_{it} (ΔTR_{it} / ΔDT_{it}) (l)	c12	2.2430	7.48
Initial tolerable schedule delay for DT (e) (prescriptive information)	c13	7.2584	7.17
Initial tolerable schedule delay for DT (l) (prescriptive information)	c14	6.9338	5.49
Pre-trip R initial relative indifference band (descriptive information)	a1	0.2789	7.82
En-route R initial relative indifference band (descriptive information)	a2	0.1769	4.92
R user characteristics / GENDER (r)	a3	-4.6752	-4.62
R information reliability 1 / ERRO (r)	a4	-3.5511	-4.86
R information reliability 2 / ERRU (r)	a5	-4.8384	-6.16
R schedule delay 1 / SDPE (r)	a6	-2.2540	-7.77
R schedule delay 2 / SDPL (r)	a7	-2.9023	-4.92
Pre-trip R initial relative indifference band (prescriptive information)	a8	0.3820	6.38
En-route R initial relative indifference band (prescriptive information)	a9	0.2380	8.59
Pre-trip R initial minimum trip time saving (descriptive information)	b1	3.8696	4.19
En-route R initial minimum trip time saving (descriptive information)	b2	2.9008	6.82

TABLE 5.12 (CONT'D): THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 1)

Component / Attribute	Param.	Estimates	t
R user characteristics / GENDER (m)	b3	-2.9000	-11.89
R information reliability 1 / ERRO (m)	b4	-0.2906	-5.85
R information reliability 2 / ERRU (m)	b5	-1.9378	-4.05
R schedule delay 1 / SDPE (m)	b6	-2.5836	-5.95
R schedule delay 2 / SDPL (m)	b7	-4.8408	-5.21
Pre-trip R initial minimum trip time saving (prescriptive information)	b8	4.1935	4.61
En-route R initial minimum trip time saving (prescriptive information)	b9	0.4970	7.60
Standard Deviation for DT decision	σ_D	0.1574	4.58
Standard Deviation for pre-trip R decision (r)	σ_{1r}	4.3540	6.27
Standard Deviation for en-route R decision (r)	σ_{2r}	0.6423	6.30
Covariance for the contemporaneous correlation of DT and pre-trip route decisions (r)	$\gamma_{D1,r}$	8.3882	7.67
Covariance for the serial correlation between DT decisions on days t and t+1	γ_D	2.5801	11.53
Standard Deviation for pre-trip R decision (m)	σ_{1m}	4.8408	5.52
Standard Deviation for en-route R decision (m)	σ_{2m}	5.0050	6.69
Covariance for the contemporaneous correlation of DT and pre-trip route decisions (m)	$\gamma_{D1,m}$	3.2261	5.39
Covariance for the Serial Correlation between pre-trip and en-route route decisions (m)	γ_{2m}	0.8055	9.04
Covariance for the Serial Correlation between en-route route decisions (m)	γ_{3m}	4.8372	5.25
Covariance for the Serial Correlation between pre-trip R decisions on days t and t+1 (m)	γ_{1m}	1.6103	4.82
Covariance for the Serial Correlation between en-route route decisions on days t and t+1 (m)	γ_{4m}	4.8415	4.99
Log-likelihood at convergence	-2937.41		

The parameters that capture the effects of real-time information quality, both over-estimation and under-estimation error of the actual travel time, are c7 through c10 for the departure time switching decision. The estimation results yield positive signs for the parameters c7 through c10, indicating that commuters tend to engage in less departure time switching after experiencing lower reliability of the real-time information.

The short term adjustment in response to the most recently experienced travel time change resulting from a departure time change is captured by parameters c11 and c12, the estimated value of which has correct sign and reasonable magnitude. If commuters have recently experienced a substantial increase in travel time as a result of a small adjustment in departure time, they seem likely to tolerate greater schedule delay in subsequent decisions (i.e., are less likely to switch), as a way of absorbing the possibly large fluctuations in trip time associated with small adjustments in departure time.

As for the route switching models, the parameters that capture user characteristics is a3 for the relative indifference band and b3 for the minimum trip time saving. The estimated values have negative signs, indicating that male commuters tend to switch routes more frequently than females both pre-trip and en-route.

The parameters that capture the effects of real-time information quality, both over-estimated and under-estimated errors of the actual travel time, are a4 and a5 for the relative indifference band and b4 and b5 for the minimum trip time saving. The estimation results yielded negative signs for all four parameters, indicating that travelers tend to more readily switch routes both pre-trip and en-route when the information system has low reliability.

The parameters that capture the effect of the commuter's "goal" (the preferred arrival time) at each decision node, both early-side and late-side schedule delay, are a6 and a7 for the relative indifference band and b6 and b7 for the minimum trip time saving. The estimated values of these parameters have negative signs, indicating that commuters tend to switch their route both pre-trip and en-route in response to higher differences between the "predicted" arrival time (based on current time and travel time from current location to the destination as provided by the system) at a given decision node and the preferred arrival time. The lower absolute value of parameter a6 compared to that of a7, and the lower absolute value of b6 than that of b7 further suggest that commuters are more prone to switch their travel paths when they perceived late arrival following the current path than when they perceived early arrival following the current path.

The estimates of σ's, γ_D, $\gamma_{D1,r}$, and $\gamma_{D1,m}$ are significant at reasonable confidence level, suggesting that serial correlation of departure time decision and the contemporaneous correlation between departure time and pre-trip route decisions should be considered. The estimates of γ_{1m}, γ_{2m}, γ_{3m}, and γ_{4m} are all significant at reasonable confidence level, which confirms the need to explicitly incorporate serial correlation in the error specification of the minimum trip time saving term. The covariance terms (γ's) are generally much smaller than the variance terms. Moreover, the estimates of covariance terms for the departure time and route switching model indicate

positive correlation between the unobserved disturbances. These model estimation results are found to be consistent with the results obtained by Mahmassani and Liu (1997).

Turning now to the main purpose of this experiment, we are interested in characterizing the differences in ATIS user switching behavior under the experimental factors of information quality, as these differences might be reflected by the initial tolerable schedule delays and the relative and minimum indifference bands. In Model 1, binary indicator initial indifference bands have been estimated for: (1) descriptive information; and (2) prescriptive information.

The initial tolerable schedule delay for the late-side is smaller than that for the early-side in the departure time decision for both prescriptive and descriptive information. This reveals that commuters are more prone to switch their departure time with late arrival than with early arrival. It implies that the commuters implicitly increase their anxiety level, as arriving late at work negatively affects commuters' daily work schedule, performance evaluation, and morale. The magnitudes of c1 and c2 for descriptive information are 12.1 and 7.1 minutes, higher than c13 and c14 for prescriptive information, which are 7.3 and 6.9 minutes, respectively. These two pairs of estimated values suggest that commuters under prescriptive information are less inclined to adjust their departure time than those under descriptive information.

For the route switching indifference bands, the estimated values of the initial relative indifference band for descriptive information reveal that an average of about 28% for pre-trip route decision (parameter a1 in Table 5.12) and 18% for en-route path decision (parameter a2) trip time saving relative to the travel time along the current path is needed to trigger a route switch under perfect information supply, and no schedule delay. The corresponding estimated values for prescriptive information is 38% for pre-trip route decision (parameter a8) and 24% for en-route path decisions (parameter a9). This result indicates that commuters tend to be more hesitant to switch route pre-trip than en-roue. It also shows that commuters under prescriptive information are less inclined to adjust both their pre-trip and en-route routes than those under descriptive information.

Both the estimated values of the initial minimum trip time saving for pre-trip switching decisions (parameter b1 for descriptive information and b8 for prescriptive information in Table 5.12) indicate that an absolute minimum of about 4 minutes of trip time saving is required for a route switch to occur, under perfect information supply and no schedule delay. On the other hand, only about 3 minutes of trip time saving is required for a en-route path switch to occur for descriptive information (parameter b2) and about half a minute for prescriptive information (parameter b9). The higher value of parameter a1 compared to that of a2, a8 compared to a9, b1 compared to b2, and b8 compared to b9, further reflect that commuters switch their pre-trip route more cautiously than en-route. A relatively lower b9 compared to b2 reveal that under

prescriptive real-time information, commuters require little time improvement to switch path en-route.

The estimation results of Model 2 for three consecutive days are presented in Table 5.13. All of the parameters for the departure time switching decisions that capture the effects of user characteristics, real-time information reliability, and the myopic adjustments in response to the most recently experienced travel time change resulting from a departure time switch have correct signs and reasonable magnitudes, consistent with those in Model 1. As for the route switching models, the parameters that capture user characteristics, real-time information quality, and commuter's "goal" at each decision node have correct signs and reasonable magnitudes as in Model 1 as well. Furthermore, the estimates of the serial correlation and the contemporaneous correlation among departure time, and pre-trip and en-route route decisions are significant at reasonable confidence level. In summary, these model estimation results are found to be consistent with the results obtained from Model 9 and from Experiment 2.

Following the specification of Model 2 (equations 5.4, 5.5, and 5.6), the differences in ATIS user switching behavior under the experimental factor of information quality as represented by the initial tolerable schedule delays and the relative and minimum indifference bands have the following four controlled levels: (1) prevailing information; (2) predicted information; (3) random information; and (4) perturbed information.

The initial tolerable schedule delay for the late-side is smaller than that for the early-side in the departure time decision for all four levels of information reliability (i.e., $c1 > c2$; $c13 > c14$; $c15 > c16$; and $c17 > c18$), consistent with the findings from Model 9. For the early-side schedule delay, the estimated value of the initial indifference band is the lowest for predicted information, followed by random information, then prevailing information, and the highest for perturbed information, ranging from around eleven minutes to eighteen-and-a-half minutes. The same order of rankings is not observed for the late-side schedule delay. In this case, the estimated value of the initial indifference band is the lowest for perturbed information, followed by random information, then predicted information, and the highest for prevailing information, ranging from around five-and-a-half minutes to eleven-and-a-half minutes.

For the route switching indifference bands under all but one level, the initial indifference band for pre-trip route decision is wider than that for the en-route path switching, for both the relative and the absolute minimum bands. This level is the predicted information, under which both the relative and absolute minimum initial indifference band for pre-trip route decision is narrower than that for the en-route path switching, respectively (that is, $a8 < a9$; and $b8 < b9$). The estimated initial relative indifference band for pre-trip route decision varies from 20.4% to 47.8%, with perturbed information at the low end, followed by predicted information, then

prevailing information, and random information at the high end. The same hierarchy, however, can not be applied to the initial relative indifference band for en-route path switching. The estimated en-route indifference band ranges from 16.0% to 48.8%, with perturbed information at the low end, followed by prevailing information, then random information, and predicted information at the high end.

As for the initial absolute minimum trip time savings, no consistent patterns of ranking order are observed as well. The estimated value for pre-trip route decision is the lowest for predicted information, followed by prevailing information, then random information, and the highest for perturbed information, ranging from around one minute to four-and-a-half minutes. Meanwhile, the estimated value for en-route path switching is found to vary between one-and-a-half minutes and four minutes, with perturbed information at the low end, followed by predicted information, then prevailing information, and random information at the high end.

TABLE 5.13: THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 2)

Component / Attribute	Param	Estimates	t
Initial tolerable schedule delay for DT (e) (prevailing information)	c1	18.0653	7.71
Initial tolerable schedule delay for DT (l) (prevailing information)	c2	11.6129	7.43
DT user characteristics 1 / AGE (e)	c3	4.5179	7.19
DT user characteristics 1 / AGE (l)	c4	1.1669	6.09
DT user characteristics 2 / GENDER (e)	c5	-3.0636	-5.49
DT user characteristics 2 / GENDER (l)	c6	-0.4936	-8.37
DT information reliability 1 / SERRO (e)	c7	3.8714	7.14
DT information reliability 1 / SERRO (l)	c8	3.2452	11.54
DT information reliability 2 / SERRU (e)	c9	0.4747	4.58
DT information reliability 2 / SERRU (l)	c10	0.0472	8.52
DT myopic / λ_{it} (ΔTR_{it} / ΔDT_{it}) (e)	c11	3.7107	9.78
DT myopic / λ_{it} (ΔTR_{it} / ΔDT_{it}) (l)	c12	3.3515	7.71
Initial tolerable schedule delay for DT (e) (predicted information)	c13	10.8055	5.82
Initial tolerable schedule delay for DT (l) (predicted information)	c14	10.1613	4.30

TABLE 5.13 (CONT'D): THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 2)

Component / Attribute	Param.	Estimates	t
Initial tolerable schedule delay for DT (e) (random information)	c15	15.1610	11.05
Initial tolerable schedule delay for DT (l) (random information)	c16	9.1939	5.68
Initial tolerable schedule delay for DT (e) (perturbed information)	c17	18.5475	4.71
Initial tolerable schedule delay for DT (l) (perturbed information)	c18	5.3227	6.05
Pre-trip R initial relative indifference band (prevailing information)	a1	0.4667	7.19
En-route R initial relative indifference band (prevailing information)	a2	0.2310	11.74
R user characteristics / GENDER (r)	a3	-0.6466	-4.32
R information reliability 1 / ERRO (r)	a4	-5.0000	-9.74
R information reliability 2 / ERRU (r)	a5	-0.4954	-5.12
R schedule delay 1 / SDPE (r)	a6	-0.8040	-6.96
R schedule delay 2 / SDPL (r)	a7	-2.9020	-5.14
Pre-trip R initial relative indifference band (predicted information)	a8	0.3784	8.86
En-route R initial relative indifference band (predicted information)	a9	0.4884	4.39
Pre-trip R initial relative indifference band (random information)	a10	0.4784	7.91
En-route R initial relative indifference band (random information)	a11	0.3499	5.02
Pre-trip R initial relative indifference band (perturbed information)	a12	0.2046	8.50
En-route R initial relative indifference band (perturbed information)	a13	0.1602	5.79
Pre-trip R initial minimum trip time saving (prevailing information)	b1	2.7436	4.06

TABLE 5.13 (CONT'D): THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 2)

Component / Attribute	Param.	Estimates	t
En-route R initial minimum trip time saving (prevailing information)	b2	1.9357	7.50
R user characteristics / GENDER (m)	b3	-4.0327	-6.37
R information reliability 1 / ERRO (m)	b4	-0.0047	-1.87
R information reliability 2 / ERRU (m)	b5	-0.9694	-8.50
R schedule delay 1 / SDPE (m)	b6	-3.3869	-5.16
R schedule delay 2 / SDPL (m)	b7	-4.3546	-6.71
Pre-trip R initial minimum trip time saving (predicted information)	b8	1.1276	11.38
En-route R initial minimum trip time saving (predicted information)	b9	1.7775	4.04
Pre-trip R initial minimum trip time saving (random information)	b10	4.3555	5.45
En-route R initial minimum trip time saving (random information)	b11	4.0328	4.40
Pre-trip R initial minimum trip time saving (perturbed information)	b12	4.6775	6.09
En-route R initial minimum trip time saving (perturbed information)	b13	1.6113	5.11
Standard Deviation for DT decision	σ_D	1.9339	5.32
Standard Deviation for pre-trip R decision (r)	σ_{1r}	3.3873	11.70
Standard Deviation for en-route R decision (r)	σ_{2r}	1.7727	11.35
Covariance for the contemporaneous correlation of DT and pre-trip route decisions (r)	$\gamma_{D1,r}$	3.8707	5.55
Covariance for the serial correlation between DT decisions on days t and t+1	γ_D	3.7097	10.34
Standard Deviation for pre-trip R decision (m)	σ_{1m}	4.1942	4.86
Standard Deviation for en-route R decision (m)	σ_{2m}	3.7105	5.16
Covariance for the contemporaneous correlation of DT and pre-trip route decisions (m)	$\gamma_{D1,m}$	0.8037	6.89
Covariance for the Serial Correlation between pre-trip and en-route route decisions (m)	γ_{2m}	4.3561	5.81

TABLE 5.13 (CONT'D): THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 2)

Component / Attribute	Param.	Estimates	t
Covariance for the Serial Correlation between en-route route decisions (m)	γ_{3m}	0.8012	7.91
Covariance for the Serial Correlation between pre-trip R decisions on days t and t+1 (m)	γ_{1m}	2.5828	6.33
Covariance for the Serial Correlation between en-route route decisions on days t and t+1 (m)	γ_{4m}	4.3547	11.62
Log-likelihood at convergence		-2905.47	

The estimation results of Model 3 for three consecutive days are presented in Table 5.14. All of the parameters for the departure time switching decisions that capture the effects of user characteristics, real-time information quality, and the myopic adjustments in response to the most recently experienced travel time change resulting from a departure time switch have correct signs and reasonable magnitudes, consistent with those in Models 1 and 2. As for the route switching models, the parameters that capture user characteristics, real-time information quality, and commuter's "goal" at each decision node have correct signs and reasonable magnitudes as in Models 1 and 2 as well. Furthermore, the estimates of the serial correlation and the contemporaneous correlation among departure time, and pre-trip and en-route route decisions are significant at reasonable confidence level. In summary, these model estimation results are found to be consistent with the results obtained from Models 1 and 2.

Following the specification of Model 3 (equations 5.7, 5.8, and 5.9), the differences in ATIS user switching behavior under the experimental factor of feedback as represented by the initial tolerable schedule delays and the relative and minimum indifference bands have the following three controlled levels: (1) feedback on own experience; (2) feedback on recommendation; and (3) feedback on actual best route.

The initial tolerable schedule delay for the late-side is smaller than that for the early-side in the departure time decision for all three levels of information reliability (i.e., $c1 > c2$; $c13 > c14$; and $c15 > c16$), consistent with the findings from Model 9. For the early-side schedule delay, the estimated value of the initial indifference band is the lowest for feedback on recommendation, followed by feedback on own experience, then feedback on actual best route, ranging from around thirteen-and-a-half minutes to fifteen-and-a-half minutes. The same order of rankings is not observed for the late-side schedule delay. In this case, the estimated value of the initial indifference band is the lowest for feedback on actual best route, followed by feedback on

recommendation, and the highest for feedback on own experience, ranging from around four-and-a-half minutes to twelve-and-a-half minutes.

For the route switching indifference bands under all but one level, the initial indifference band for pre-trip route decision is wider than that for the en-route path switching, for both the relative and the absolute minimum bands. This level is the feedback on actual best route, under which both the relative and absolute minimum initial indifference band for pre-trip route decision is narrower than that for the en-route path switching, respectively (that is, a10 < a11; and b10 < b11). The estimated initial relative indifference band for pre-trip route decision varies from 39.2% to 50.8%, with feedback on actual best route at the low end, followed by feedback on recommendation, and feedback on own experience at the high end. The same hierarchy can be applied to the initial relative indifference band for en-route path switching as well. The estimated en-route indifference band ranges from 7.2% to 35.5%.

As for the initial absolute minimum trip time savings, no consistent patterns of ranking order are observed between pre-trip route selection and en-route path switching. The estimated value for pre-trip route decision is the lowest for feedback on actual best route, followed by feedback on recommendation, then feedback on own experience, ranging from around two minutes to five minutes. Meanwhile, the estimated value for en-route path switching is found to vary between one minute and five minutes, with feedback on recommendation at the low end, followed by feedback on actual best route, and feedback on own experience at the high end.

TABLE 5.14: THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 3)

Component / Attribute	Param.	Estimates	t
Initial tolerable schedule delay for DT (e) (feedback on own experience)	c1	14.5159	5.13
Initial tolerable schedule delay for DT (l) (feedback on own experience)	c2	12.7452	4.57
DT user characteristics 1 / AGE (e)	c3	5.0045	6.69
DT user characteristics 1 / AGE (l)	c4	3.2303	7.86
DT user characteristics 2 / GENDER (e)	c5	-4.1957	-6.85
DT user characteristics 2 / GENDER (l)	c6	-0.1381	-5.07
DT information reliability 1 / SERRO (e)	c7	1.6142	5.47
DT information reliability 1 / SERRO (l)	c8	1.5451	7.90
DT information reliability 2 / SERRU (e)	c9	3.7066	7.71

TABLE 5.14(CONT'D): THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 3)

Component / Attribute	Param.	Estimates	t
DT information reliability 2 / SERRU (l)	c10	3.3567	7.79
DT myopic / λ_{it} (ΔTR_{it} / ΔDT_{it}) (e)	c11	1.9433	7.22
DT myopic / λ_{it} (ΔTR_{it} / ΔDT_{it}) (l)	c12	0.0615	4.64
Initial tolerable schedule delay for DT (e) (feedback on recommendation)	c13	13.7112	11.63
Initial tolerable schedule delay for DT (l) (feedback on recommendation)	c14	5.8064	4.48
Initial tolerable schedule delay for DT (e) (feedback on actual best)	c15	15.6443	6.15
Initial tolerable schedule delay for DT (l) (feedback on actual best)	c16	4.3548	4.08
Pre-trip R initial relative indifference band (feedback on own experience)	a1	0.5077	4.74
En-route R initial relative indifference band (feedback on own experience)	a2	0.3552	8.22
R user characteristics / GENDER (r)	a3	-3.3865	-7.05
R information reliability 1 / ERRO (r)	a4	-1.6099	-5.24
R information reliability 2 / ERRU (r)	a5	-3.7117	-7.07
R schedule delay 1 / SDPE (r)	a6	-0.6401	-4.72
R schedule delay 2 / SDPL (r)	a7	-4.0378	-6.66
Pre-trip R initial relative indifference band (feedback on recommendation)	a8	0.4014	4.73
En-route R initial relative indifference band (feedback on recommendation)	a9	0.3260	5.62
Pre-trip R initial relative indifference band (feedback on actual best)	a10	0.0717	7.16
En-route R initial relative indifference band (feedback on actual best)	a11	0.3916	6.77
Pre-trip R initial minimum trip time saving (feedback on own experience)	b1	5.0009	9.07
En-route R initial minimum trip time saving (feedback on own experience)	b2	4.9977	4.53
R user characteristics / GENDER (m)	b3	-0.3206	-2.26
R information reliability 1 / ERRO (m)	b4	-2.2568	-6.96
R information reliability 2 / ERRU (m)	b5	-0.4753	-5.28
R schedule delay 1 / SDPE (m)	b6	-3.3844	-7.66
R schedule delay 2 / SDPL (m)	b7	-2.9001	-6.47

TABLE 5.14(CONT'D): THE ESTIMATION RESULTS FOR THE JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND BASED ON THREE-DAY COMMUTING DATA (MODEL 3)

Component / Attribute	Param.	Estimates	t
Pre-trip R initial minimum trip time saving (feedback on recommendation)	b8	2.2558	4.68
En-route R initial minimum trip time saving (feedback on recommendation)	b9	1.0185	10.42
Pre-trip R initial minimum trip time saving (feedback on actual best)	b10	2.1029	7.11
En-route R initial minimum trip time saving (feedback on actual best)	b11	4.6757	11.72
Standard Deviation for DT decision	σ_D	1.4459	4.89
Standard Deviation for pre-trip R decision (r)	σ_{1r}	2.4343	4.95
Standard Deviation for en-route R decision (r)	σ_{2r}	5.0047	4.08
Covariance for the contemporaneous correlation of DT and pre-trip route decisions (r)	$\gamma_{D1,r}$	5.4904	6.18
Covariance for the serial correlation between DT decisions on days t and t+1	γ_D	1.9310	11.78
Standard Deviation for pre-trip R decision (m)	σ_{1m}	4.8400	6.65
Standard Deviation for en-route R decision (m)	σ_{2m}	4.9970	5.82
Covariance for the contemporaneous correlation of DT and pre-trip route decisions (m)	$\gamma_{D1,m}$	2.9016	6.77
Covariance for the Serial Correlation between pre-trip and en-route route decisions (m)	γ_{2m}	0.9945	4.67
Covariance for the Serial Correlation between en-route route decisions (m)	γ_{3m}	3.2306	4.78
Covariance for the Serial Correlation between pre-trip R decisions on days t and t+1 (m)	γ_{1m}	4.6752	7.37
Covariance for the Serial Correlation between en-route route decisions on days t and t+1 (m)	γ_{4m}	3.8741	4.90
Log-likeihood at convergence	-2936.51		

SUMMARY

The data obtained from the laboratory experiments using the dynamic interactive simulator have provided a rich observational basis for the study of traveler decision dynamics in response to real-time traffic information. The exploratory analysis of traveler behavior focused on three aspects of trip-making behavior for morning commute: (1) the travelers' departure time and route choice as well as the variation that they exhibited from day to day; (2) the frequency of user compliance decisions with route-based information; and (3) the frequency of non-switching decisions based

on those from the preceding trip, as a measure of the overall "satisfaction" of trip-making experience. The following three main models of commuter behavior have been developed and calibrated:

(1) Frequency models of ATIS user compliance on pre-trip and en-route path decisions. These models consist of the number of route decisions in a trip, which are in compliance with the real-time information, following the Poisson distribution.

(2) Frequency models of commuters' decisions to not adjust pre-trip departure time and route selection as well as en-route path switching as a reflection of their satisfaction with the current commuting conditions. These models consist of the number of non-switching decisions in a trip as compared with those from the preceding trip, again following the Poisson distribution.

(3) Day-to-day dynamic models of joint departure time and route switching indifference bands. These models consist of dynamically varying indifference bands with systematically varying mean values and normally distributed random components, which have been formulated and calibrated using a generalized multinomial probit modeling framework.

Several substantive conclusions have been obtained in this chapter as summarized hereafter.

(1) The accuracy of the real-time information is a significant variable that influences commuters' compliance with route choice information. The commuters are less inclined to comply with real-time information when the system provides under-estimated or over-estimated trip times. Likewise, the commuters are less inclined to be satisfied with inaccurate real-time information.

(2) A lower rate of compliance is likely to be achieved under real-time information if commuters recently experienced significant congestion, such as getting stuck in traffic in the preceding highway segment. The commuters tend to be less satisfied with the same negative experience.

(3) Compliance is less likely to be achieved when commuters experience high schedule delays (i.e., difference between the "predicted" arrival time and individual preferred arrival time). Furthermore, they are less likely to be compliant when they experience late arrival to work than when they experience early arrival to work.

(4) When experiencing high variability in trip time, the commuters tend to be less satisfied with their previous trip-making decisions.

(5) Commuters tend to comply more with real-time information when no switching is required, i.e., when the current path is indeed the path suggested/recommended by the system. A much lesser compliance is likely to be achieved in situations where switching from the current path is required to follow the "best" path. This aversion to switch, when instrumented as a "cost" of switching, is found to be a particularly strong factor. A similar "cost" of switching is found to be significant in the switching models under the bounded rationality framework, in the form of an indifference band.

(6) The greater the benefits of complying with real-time information (i.e., trip time improvement), the more inclined the commuters are to comply.

(7) A trend of increasing satisfaction (or diminishing propensity to switch) from day to day seems to be present for commuters under real-time information, indicating that there may exist a pattern of convergence in commuters' departure time and route choices over time.

(8) A higher rate of compliance is likely to be achieved under real-time information when commuters are provided with prescriptive or normative information than when they are provided with descriptive information. Likewise, commuters are more inclined to be "satisfied" under the real-time information when supplied with prescriptive information than with descriptive information.

(9) There exists a hierarchy of systems of varying information quality under which different levels of compliance could be achieved. In the context of our experiment, the more reliable the information is, the higher rate of compliance is observed. Under this hierarchy, commuters tend to comply most with predicted information, followed by prevailing information, then perturbed information, differential predicted, differential prevailing, and least with random information. The same hierarchy is found to be valid for the model of user satisfaction under which commuters are most likely to be content with predicted information and least likely with random information.

(10) The type of post-trip feedback made available to commuters influences their behavior of compliance and satisfaction. ATIS systems providing feedback with either the recommended path or the actual best path are more likely to acquire a higher rate of user compliance and satisfaction than systems with feedback on own experience only. Tripmakers receiving feedback with the actual best path tend to comply more than those receiving feedback with the path recommended by the system. Tripmakers receiving feedback with the path recommended by the system tend to be less content than those receiving feedback with the actual best path *ex post facto*. Commuters are least prone to comply or be satisfied when the only feedback available is their own experience.

(11) In the pre-trip departure time switching decision model, older commuters tend to tolerate greater schedule delay than younger ones. Also, female commuters exhibit a wider mean indifference band than male commuters for pre-trip departure time and route decisions as well as en-route path switching decision.

(12) The reliability of the real-time information is a significant variable that influences commuters' pre-trip departure time and route switching decisions as well as en-route path switching decision. The commuters tend to keep their routine departure time, but change their routes both pre-trip and en-route in response to low reliability of the real-time information system perceived by the commuters. Moreover, tripmakers become more prone to switch routes when the system provides under-estimated trip time information than when the system provides over-estimated trip times. Compared to the findings obtained from previous studies of commuter behavior without real-time information, the experimental results suggest that real-time information availability tends to induce greater frequency of route switching, both pre-trip and en-route.

(13) Commuters are inclined to tolerate greater schedule delay (associated with a particular departure time decision) if they have recently experienced a substantial increase in travel time resulting from a small adjustment in departure time.

(14) Commuters tend to switch their route both pre-trip and en-route in response to higher differences between the "predicted" arrival time at a given decision node and their own

preferred arrival time. Furthermore, travelers become more prone to switch routes when they perceive late arrival by following the current path than when they perceive early arrival by following the current path.

(15) The estimates of all variances terms and covariance terms for the minimum trip time saving component are statistically significant in the route switching models, which confirms the need to incorporate serial correlation in the specification. Moreover, the serial correlation effects between pre-trip and en-route decisions are different from those across en-route decisions.

(16) The estimates of all variance terms and covariance terms for departure time and pre-trip route decisions are statistically significant in the joint departure time and route switching models. The obtained result confirms the need to incorporate contemporaneous correlation between departure time and pre-trip route decisions.

(17) The initial tolerable schedule delay for the late side is smaller than that for the early side in the departure time decision. This strongly reveals that commuters are more prone to switch their departure time with late arrival than with early arrival. In addition, travelers are more inclined to switch their departure time under descriptive information than prescriptive information, for both the late side and the early side.

(18) The initial relative difference band for pre-trip route adjustment is wider than that for en-route path switching. This indicates that commuters tend to be more hesitant to switch route pre-trip than en-roue. The only exceptions are when the commuters are provided with predicted information and with feedback on actual best path. It also shows that commuters under prescriptive information are less inclined to adjust both their pre-trip and en-route routes than those under descriptive information.

CHAPTER 6: CONCLUDING REMARKS

Three main objectives have been achieved in this research. The first main objective was to design interactive experiments to observe commuters' pre-trip path and departure time choice decisions and en-route route diversion decisions over time, and to develop a special-purpose interactive travel simulator for conducting these experiments as well as data collection. A novel research methodology to study the dynamics of commuter behavior in response to different information strategies of varying information quality in a large-scale interactive laboratory-like setting that was internally and externally consistent with real-world traffic conditions has been designed. Furthermore, a dynamic interactive simulator with the capability for real-time interaction with and among multiple driver participants in a traffic network under different ATIS strategies has been developed. This simulator considered both the supply-side system performance as influenced by driver response to real-time traffic information and the demand-side driver behavior as influenced by real-time traffic information based on system performance.

The second main objective was to conduct the laboratory experiments using the simulator developed and to collect data from which the observational basis could be provided for the development of user response models that could be used in simulation-assignment tools to evaluate network performance under real-time information. Actual commuter travel behavior data have been collected from these laboratory experiments using the dynamic interactive simulator and they have been used for the development and calibration of behavioral models in the study of commuter decision dynamics under ATIS.

The last main objective was to formulate behavioral frameworks of driver response under the provision of real-time traffic information and to build behaviorally realistic decision process models based on the data gathered from the experiments. Theoretical constructs have been developed for representing commuter behavior with regard to (i) representing commuters' compliance to, as well as satisfaction with, the real-time traffic information system and the related trip-making experience, (ii) describing commuters' departure time, pre-trip route and en-route path switching decisions behavior under real-time information, and (iii) capturing day-to-day learning and travel time prediction processes of commuters in response to actual experience and exogenous information. Models of ATIS user response to different information strategies in the areas of: (i) user compliance, (ii) user satisfaction, and (iii) user joint departure and route switching decisions have been calibrated using the data obtained from the experiments. These models form an essential component for use within evaluation frameworks (e.g., simulation-assignment models) for assessing the effectiveness of different real-time information strategies.

This chapter presents a summary of the key findings and discusses future research needs in the area of commuter behavior under ATIS. The first section provides the summary of the key

findings and the conclusion of the previous chapters. The second section discusses possible applications and future research directions.

SUMMARY AND CONCLUSIONS

A dynamic travel simulator has been developed that offers the capability for real-time interaction with and among multiple driver participants in a traffic network under different ATIS strategies. This simulator allows several drivers to "drive" through the network while responding to real-time traffic information, interact with other drivers and contribute to system evolution. It considered both the supply-side system performance as influenced by driver response to real-time traffic information and the demand-side driver behavior as influenced by real-time traffic information based on system performance. Its "engine" was a traffic flow simulator and ATIS information generator that displayed information consistent with the processes actually taking place in the (simulated) traffic system. The decisions made by the driver participants were fed directly to the simulator, and as such influenced the traffic system itself and the subsequent stream of information stimuli provided to the participants.

A series of interactive experiments has been conducted to examine commuters' trip-making behavior in response to different information strategies of varying information quality using this dynamic travel simulator as discussed in Chapter 3. Four important aspects of tripmaker behavior in response to real-time traffic information were investigated:

(1) Compliance behavior of ATIS users. The key factors that influence traveler compliance decisions under real-time information were investigated. Models of user compliance to information received were calibrated. This experiment aimed to investigate the association between switching decisions and compliance decisions and to determine how the accuracy and reliability of supplied information to the users affect the overall compliance rate.

(2) ATIS user satisfaction. The objective was to develop a user satisfaction model that represented the level of satisfaction of tripmakers in achieving their commuting purposes under real-time information. This objective was focused on understanding how tripmakers' day-to-day decision-making process might evolve over time as they become more familiar with the real-time information and the traffic system. In particular, this experiment attempted to relate the number of switching decisions made by commuters per trip to information quality and schedule delay as well as to explore any trends of convergence to a satisfactory trip plan.

(3) Trip-making behavior of users under different ATIS strategies. The objective here was to investigate how different potential ATIS information strategies, covering a wide range of information quality, affect commuter travel decisions. In this regard, the following three aspects of ATIS information strategies were examined in this experiment:

(i) Nature of information: prescriptive; descriptive.

(ii) Information quality (trip time information based on): reliable prediction; prevailing condition; perturbed prediction; differential predicted; differential prevailing; random.

(iii) Feedback: own trip experience; recommended; actual best.

(4) Dynamic switching models of ATIS users. The objective was to investigate to what extend and how ATIS information quality influence tripmakers' pre-trip and en-route choice behavior. This experiment followed the discrete choice modeling framework developed by Mahmassani and Liu (1997) to compare and validate the role that travelers' own past experience with the traffic information system played in their decision making process, and the interaction effects between travelers' own past experiences and real-time traffic information system. Under this framework, indifference bands for switching decisions in response to different information strategies were calibrated and the results were assessed comparatively.

From the interactive experiments, several substantive conclusions have been obtained as summarized hereafter.

(1) The accuracy of the real-time information was a significant variable that influenced commuters' compliance with route choice information. The commuters were less inclined to comply with real-time information when the system provided under-estimated or over-estimated trip times. Likewise, the commuters were less inclined to be satisfied with inaccurate real-time information.

(2) A lower rate of compliance was likely to be achieved under real-time information if commuters recently experienced significant congestion, such as getting stuck in traffic in the preceding highway segment. The commuters tended to be less satisfied with the same negative experience.

(3) Compliance was less likely to be achieved when commuters experienced high schedule delays (i.e., difference between the "predicted" arrival time and individual preferred arrival time). Furthermore, they were less likely to be compliant when they experienced late arrival to work than when they experienced early arrival to work.

(4) When experiencing high variability in trip time, the commuters tended to be less satisfied with their previous trip-making decisions.

(5) Commuters tended to comply more with real-time information when no switching was required, i.e., when the current path was indeed the path suggested/recommended by the system. A much lesser compliance was likely to be achieved in situations where switching from the current path was required to follow the "best" path. This aversion to switch, when instrumented as a "cost" of switching, was found to be a particularly strong factor. A similar "cost" of switching was found to be significant in the switching models under the bounded rationality framework, in the form of indifference bands.

(6) The greater the benefit of complying with real-time information (i.e., trip time improvement), the more inclined the commuters were to comply.

(7) A trend of increasing satisfaction (or diminishing propensity to switch) from day to day seemed to be present for commuters under real-time information, indicating that there could exist a pattern of convergence in commuters' departure time and route choices over time.

(8) A higher rate of compliance was likely to be achieved under real-time information when commuters were provided with prescriptive or normative information than when they were provided with descriptive information. Likewise, commuters were more inclined to be "satisfied" under the real-time information when supplied with prescriptive information than with descriptive information.

(9) There existed a hierarchy of systems of varying information quality under which different levels of compliance could be achieved. In the context of our experiment, the more reliable the information was, the higher rate of compliance was observed. Under this hierarchy, commuters tended to comply most with predicted information, followed by prevailing information, then perturbed information, differential predicted, differential prevailing, and least with random information. The same hierarchy was found to be valid for the model of user satisfaction under which commuters were most likely to be content with predicted information and least likely with random information.

(10) The type of post-trip feedback made available to commuters influenced their behavior of compliance and satisfaction. ATIS systems providing feedback with either the recommended path or the actual best path were more likely to acquire a higher rate of user compliance and satisfaction than systems with feedback on own experience only. Tripmakers receiving feedback with the actual best path tended to comply more than those receiving feedback with the path recommended by the system. Tripmakers receiving feedback with the path recommended by the system tended to be less content than those receiving feedback with the actual best path *ex post facto*. Commuters were least prone to comply or be satisfied when the only feedback available was their own experience.

(11) In the pre-trip departure time switching decision model, older commuters tended to tolerate greater schedule delay than younger ones. Also, female commuters exhibited a wider mean indifference band than male commuters for pre-trip departure time and route decisions as well as en-route path switching decision.

(12) The reliability of the real-time information was a significant variable that influenced commuters' pre-trip departure time and route switching decisions as well as en-route path switching decision. The commuters tended to keep their routine departure time, but change their routes both pre-trip and en-route in response to low reliability of the real-time information system perceived by the commuters. Moreover, tripmakers became more prone to switch routes when the system provided under-estimated trip time information than when the system provided over-estimated trip times. Compared to the findings obtained from previous studies of commuter behavior without real-time information, the experimental results suggested that real-time information availability tended to induce greater frequency of route switching, both pre-trip and en-route.

(13) Commuters were inclined to tolerate greater schedule delay (associated with a particular departure time decision) if they had recently experienced a substantial increase in travel time resulting from a small adjustment in departure time.

(14) Commuters tended to switch their route both pre-trip and en-route in response to higher differences between the "predicted" arrival time at a given decision node and their own preferred arrival time. Furthermore, travelers became more prone to switch routes when they perceived late arrival by following the current path than when they perceived early arrival by following the current path.

(15) The estimates of all variances terms and covariance terms for the minimum trip time saving component were statistically significant in the route switching models, which confirmed the need to incorporate serial correlation in the specification. Moreover, the serial correlation effects between pre-trip and en-route decisions were different from those across en-route decisions.

(16) The estimates of all variance terms and covariance terms for departure time and pre-trip route decisions were statistically significant in the joint departure time and route switching models. The obtained result confirmed the need to incorporate contemporaneous correlation between departure time and pre-trip route decisions.

(17) The initial tolerable schedule delay for the late-side was smaller than that for the early-side in the departure time decision. This strongly revealed that commuters were more prone to switch their departure time with late arrival than with early arrival. In addition, travelers were more inclined to switch their departure time under descriptive information than prescriptive information, for both the late-side and the early-side.

(18) The initial relative difference band for pre-trip route adjustment was wider than that for en-route path switching. This indicated that commuters tended to be more hesitant to switch route pre-trip than en-roue. The only exceptions were when the commuters were provided with predicted information and with feedback on actual best path. It also showed that commuters under prescriptive information were less inclined to adjust both their pre-trip and en-route routes than those under descriptive information.

In summary, the principal contributions include the following five aspects:

(1) Theoretical constructs for representing commuter behavior with regard to (i) representing commuters' compliance to as well as satisfaction with the real-time traffic information system and the related trip-making experience, (ii) describing commuters' departure time, pre-trip route and en-route path switching decisions behavior under real-time information, and (iii) capturing day-to-day learning and travel time prediction processes of commuters in response to actual experience and exogenous information.

(2) A novel research methodology to study the dynamics of commuter behavior in response to different information strategies of varying information quality and credibility in a large-scale interactive laboratory-like setting, that was internally and externally consistent with real-world traffic conditions.

(3) A dynamic interactive simulator with the capability for real-time interaction with and among multiple driver participants in a traffic network under different ATIS

strategies. It considered both the supply-side system performance as influenced by driver response to real-time traffic information and the demand-side driver behavior as influenced by real-time traffic information based on system performance.

(4) Actual commuter travel behavior data collected from laboratory-like experiment using the dynamic interactive simulator. This provided an observational basis for the development and calibration of pertinent behavioral models of interest in the study of commuter decision dynamics under ATIS.

(5) Models of ATIS user response to different information strategies in the areas of: (i) user compliance, (ii) user satisfaction, and (iii) user joint departure and route switching decisions. These models form an essential component for use within evaluation frameworks (e.g., simulation-assignment models) intended to assess the effectiveness of different real-time information strategies.

DIRECTIONS FOR FUTURE RESEARCH

In this section, promising directions for further research are presented, in the areas of additional needs for behavioral research under ATIS, assessments of potential ITS benefits, and real-world full-scale ITS implementations.

Additional Need for Behavioral Research

Unlike the normally adopted utility maximization modeling framework, under which commuters are assumed to directly select the best departure time and route, the switching modeling framework postulates that commuters first decide whether to change their previous/current route or departure time, and condition upon a decision to change, to then determine their new route or departure time. Therefore, in order to develop a complete model of commuter trip-making behavior, additional choice models are needed, in addition to the boundedly-rational switching models.

Assuming one discrete choice model is incorporated to each route switch decision, and one continuous (or discretized) departure time choice model to the departure time adjustment decision, the resulting dynamic joint departure time and route switching and selection model will be quite a challenge to estimate under the multinomial probit modeling framework. It is therefore necessary to seek and advance the behavioral and econometric modeling methodologies in order to properly specify the joint decision models in response to ATIS systems as well as estimate the pertinent explanatory decision parameters. One such model that has the capability to preserve the same non-identical and non-independent properties of the random components for multinomial probit structure is the mixed-logit model. In this model, the random component of the utility function is specified by two error terms, with one assumed to have a standard type I extreme value distribution while the other one a normal distribution. This results in an error-

components model with a logit kernel, which can be estimated relatively easy using a logit simulator. A description of the mixed-logit model is included in Bhat (1997).

Further observational bases may be produced through carefully designed surveys and trip diaries conducted on actual participants of ITS Field Operational Tests (FOTs), as well as more controlled interactive experiments on tripmakers. Of particular interest here is to obtain subject responses on the World Wide Web. Internet-based data collection schemes are a relatively low cost means of conducting research and capable of reaching a broad range of potential participants. Coordination with FOTs in terms of getting real-time on-line data through electronic recording and communications technologies is warranted as well. It is also essential to study the transferability of these calibrated behavioral models to include the variability of user behavior in terms of the network size and setting (metro cities vs. suburban areas) as well as geographical location (east coast vs. mid-west).

The traveler choice dimensions in these research work may very well be expanded to areas of activity-based behavior, commuting (such as trip-chaining and flexible work time decisions), non-commuting (such as destination choice for shopping, dinner out, movies), mode choice, carpool, HOV, park & ride, public transit, and pricing, in conjunction with various ITS traffic control and information dissemination strategies. More elaborate theoretical constructs and econometric modeling should be developed, joining these choice dimensions to form integrated frameworks of travel behavior under ITS. An example of this type of integrated behavior frameworks would be a joint model of trip-chaining, purpose/activity, destination, departure time and route choices.

Assessments of ITS Benefits

The dynamic switching and selection models, once developed and calibrated using experimental data, may be implemented into network simulation models and computer simulation experiments may be conducted to study the effect of user response on the system performance, such as trip timing and path selection, and the mechanism through which users learn and adjust these decisions. Benefits of ITS systems may then be evaluated through user behavior in response to experienced congestion, and ITS supply management strategies, such as traffic control and operations, information provision, and pricing. These experiments may be conducted in the context of:

(1) Recurrent peak-hour congestion, such as morning and evening commute.

(2) Planned supply disruptions, such as major highway repair and reconstruction activities, special sporting and cultural events.

(3) Non-recurrent traffic disruptions, such as traffic accidents, signal control malfunctioning.

(4) Emergency traffic diversion and evacuation, such as when faced with natural (hurricanes, earthquakes, and landslides) and man-made disasters (major chemical spills, fast- and wide-spread medical epidemics, bomb threats, and civil unrest).

The overall network-level benefits of an ITS system should be evaluated with this incorporation of realistic and valid user models. In addition, the resulting traffic demand, both temporally and spatially, should be explored in terms of evolution patterns, final stages (existence of single or multiple user equilibria), time required to stabilize into these final stages, and associated inherent fluctuations and uncertainties.

Real World Implementation

The same calibrated and validated dynamic switching and selection models may be implemented into a dynamic network simulation and assignment model, such as the user prediction component of DYNASMART-X, ready for real-world on-line applications in the area of ATMS. Tasks to be considered in implementing models of this nature are as follows:

- Define planning and operational needs.
- Define desirable and achievable benefits as well as performance measures.
- Design systems with the considerations of the flows of information in the planning organization and decision-making processes in the operational structure.
- Define modeling and data needs.
- Development and calibration of a system of models of network configuration and traffic flow, control and operations, and user decision.
- Implement system and conduct forecast vs. actual testing, such as model consistency evaluation and resolution.
- Support actual real-time deployment and on-line operations.

APPENDIX A: PRE-EXPERIMENT QUESTIONNAIRE

TRANSPORTATION SURVEY

Thank you for participating in our survey. Please answer all questions to the best of your knowledge. All answers, of course will be kept strictly confidential, Thank you.

1. What is your age? _____ Under 20 _____ 20-39

   _____ 40-59 _____ Over 60

2. What is your gender? _____ Male _____ Female

3. What is your job title? _____

   (e.g.: Professor, Technician, Secretary)

4. How many times do you drive your car to commute each week? _____times

5. How important is it for you to not be late to work?
   _____ I am expected to arrive on time.
   _____ I am allowed to arrive up to _____ minutes late.
   _____ It does not matter if I am late

6. How many minutes before your work officially starts do you prefer to arrive at your workplace? _____ Minutes

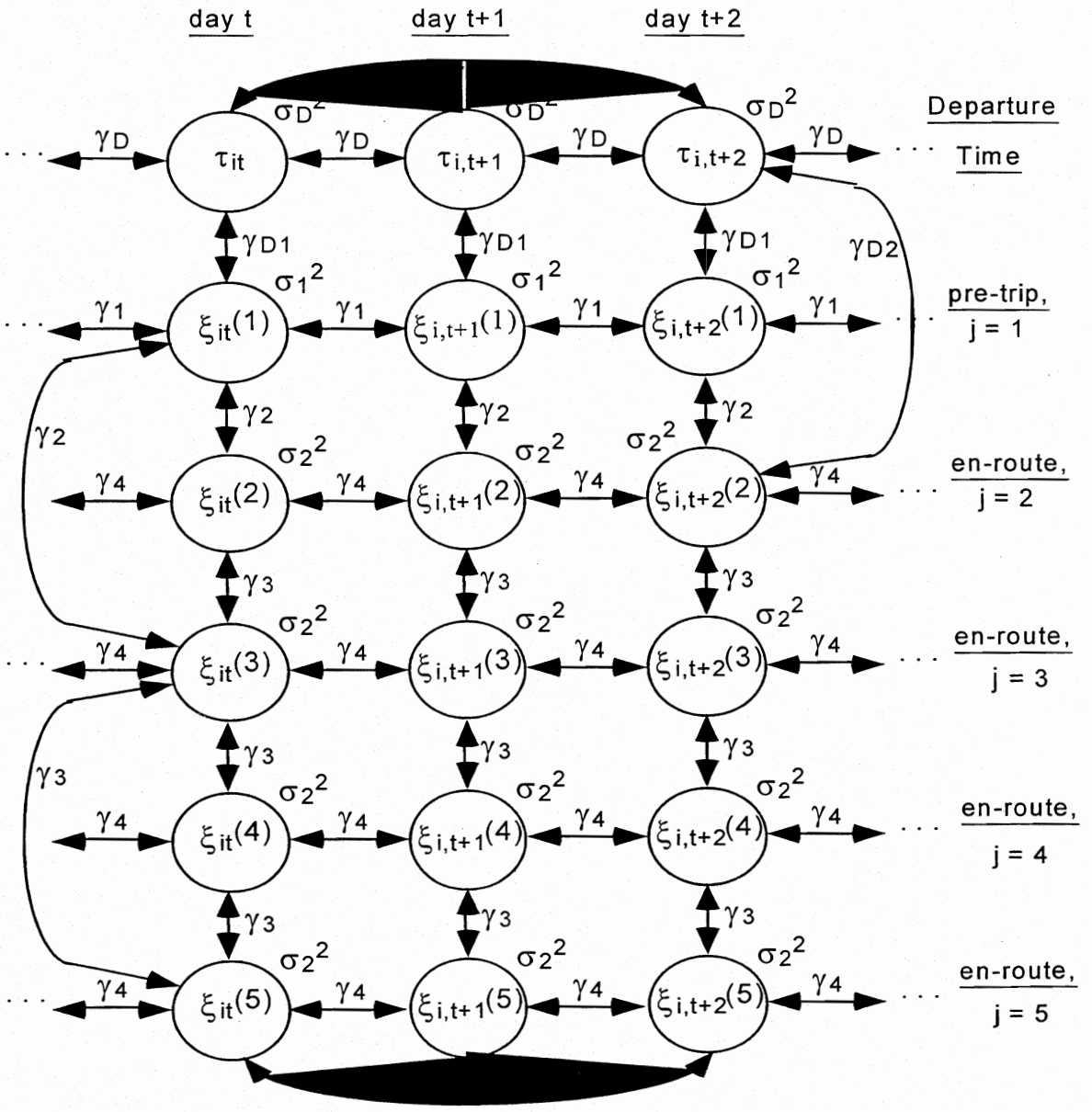
APPENDIX B: SPECIFICATION OF VARIANCE-COVARIANCE MATRIX

SPECIFICATION OF VARIANCE-COVARIANCE MATRIX FOR ERROR STRUCTURE (JOINT DEPARTURE TIME AND ROUTE SWITCHING INDIFFERENCE BAND)

$E(\tau^2_{it})$	σ^2_D	$\omega^2_{it}\,\sigma^2_{D,e} + (1-\omega_{it})^2\,\sigma^2_{D,l}$	$t = 1, \ldots, T$
$E(\xi^2_{i1t})$	σ^2_1	$W^2_{i1t}\,TTC^2_{i1t}\,\sigma^2_{1r} + (1-W_{i1t})^2\,\sigma^2_{1m}$	$t = 1, \ldots, T$
$E(\xi^2_{ijt})$	σ^2_2	$W^2_{ijt}\,TTC^2_{ijt}\,\sigma^2_{2r} + (1-W_{ijt})^2\,\sigma^2_{2m}$	$j = 2, 3, 4, 5$ $t = 1, \ldots, T$
$E(\tau_{it},\xi_{i1t})$	γ_{D1}	$\omega_{it}W_{i1t}\,TTC_{i1t}\gamma_{5r} + \omega_{it}(1-W_{i1t})\gamma_{5m} +$ $(1-\omega_{it})\,W_{i1t}\,TTC_{i1t}\,\gamma_{7r} + (1-\omega_{it})\,(1-W_{i1t})\,\gamma_{7m}$ $= W_{i1t}\,TTC_{i1t}\gamma_{D1,r} + (1-W_{i1t})\gamma_{D1,m}$	$t = 1, \ldots, T$
$E(\tau_{it},\xi_{ijt})$	γ_{D2}	$\omega_{it}W_{ijt}\,TTC_{ijt}\,\gamma_{6r} + \omega_{it}\,(1-W_{ijt})\,\gamma_{6m} +$ $(1-\omega_{it})\,W_{ijt}\,TTC_{ijt}\,\gamma_{8r} + (1-\omega_{it})\,(1-W_{ijt})\,\gamma_{8m}$ $= W_{ijt}\,TTC_{ijt}\gamma_{D2,r} + (1-W_{ijt})\gamma_{D2,m}$	$j = 2, 3, 4, 5$ $t = 1, \ldots, T$
$E(\tau_{it},\tau_{it'})$	γ_D	$\omega_{it}\,\omega_{it'}\,\gamma_{D,e} + (1-\omega_{it})(1-\omega_{it'})\,\gamma_{D,l} +$ $\omega_{it}\,(1-\omega_{it'})\,\gamma_{D,el} + (1-\omega_{it})\,\omega_{it'}\,\gamma_{D,le}$	$t, t' = 1, \ldots, T,$ $t \neq t'$
$E(\xi_{i1t},\xi_{i1t'})$	γ_1	$W_{i1t}W_{i1t'}TTC_{i1t}TTC_{i1t'}\gamma_{1r} + (1-W_{i1t})(1-W_{i1t'})\gamma_{1m}$ $+ W_{i1t}\,(1-W_{i1t'})\,TTC_{i1t}\,\gamma_{1r1m}$ $+ W_{i1t'}\,(1-W_{i1t})\,TTC_{i1t'}\,\gamma_{1m1r}$	$t, t' = 1, \ldots, T,$ $t \neq t'$
$E(\xi_{i1t},\xi_{ijt})$ $E(\xi_{ijt},\xi_{i1t})$	γ_2	$W_{i1t}W_{ijt}TTC_{i1t}TTC_{ijt}\gamma_{2r} + (1-W_{i1t})(1-W_{ijt})\,\gamma_{2m} +$ $W_{i1t}(1-W_{ijt})TTC_{i1t}\,\gamma_{2r2m} +$ $W_{ijt}(1-W_{i1t})TTC_{ijt}\,\gamma_{2m2r}$	$j = 2, 3, 4, 5$ $t = 1, \ldots, T$
$E(\xi_{ijt},\xi_{ij't})$	γ_3	$W_{ijt}W_{ij't}TTC_{ijt}TTC_{ij't}\gamma_{3r} + (1-W_{ijt})(1-W_{ij't})\gamma_{3m}$ $+ W_{ijt}\,(1-W_{ij't})\,TTC_{ijt}\,\gamma_{3r3m}$ $+ W_{ij't}\,(1-W_{ijt})\,TTC_{ij't}\,\gamma_{3m3r}$	$j, j' = 2, 3, 4, 5,$ $j \neq j'$ $t = 1, \ldots, T$
$E(\xi_{i1t},\xi_{ijt'})$ $E(\xi_{ijt},\xi_{i1t'})$ $E(\xi_{ijt},\xi_{ij't'})$	0	0	$j, j' = 2, 3, 4, 5$ $t, t' = 1, \ldots, T,$ $j \neq j', t \neq t'$
$E(\xi_{ijt},\xi_{ij't'})$	γ_4	$W_{ijt}W_{ij't'}TTC_{ijt}TTC_{ij't'}\gamma_{4r} + (1-W_{ijt})(1-W_{ij't'})\gamma_{4m} +$ $W_{ijt}\,(1-W_{ij't'})\,TTC_{ijt}\,\gamma_{4r4m}$ $+ W_{ij't'}\,(1-W_{ijt})\,TTC_{ij't'}\,\gamma_{4m4r}$	$j, j' = 2, 3, 4, 5,$ $j = j',$ $t, t' = 1, \ldots, T,$ $t \neq t'$

APPENDIX C: ERROR STRUCTURE FOR JOINT DEPARTURE TIME AND ROUTE CHOICES

Summary of error structure for joint departure time and pre-trip route selection as well as en-route path switching indifference band



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