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MODELING DRIVER'S ROUTE CHOICE BEHAVIOR UNDER THE INFLUENCE OF ADVANCE TRAVELER INFORMATION SERVICE

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PURDUE UNIVERSITY

Final Report

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Modeling Driver's Route Choice Behavior Under the Influence of Advanced Traveler Information Systems

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16. Abstract

This research consisted of two parts; this report is Volume 2 of 2 Volumes; Volume 1 is Report No. FHWA/IN/JHRP-96/10. The first part developed a set of incident clearance time prediction models for the Borman Expressway. The second part consisted of modeling driver`s route choice behavior under the influence of advanced traveler information systems.

Volume 2 of this report describes the modeling driver's route choice behavior under the influence of Advanced Traveler Information Systems. These models can help in understanding the behavior and response of travelers under the influence of Advanced Traveler Information Systems.

The products of this research project will be incorporated in the Advanced Traffic Management System that is being implemented on the Borman Expressway, a 16-mile segment of I-80 in northwest Indiana.

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IMPLEMENTATION REPORT

In this report various models of individual behavior have been developed which can be used to predict individual choice probabilities. These disaggregate models can now be used to developed aggregate forecasts. The following sections discuss the forecasts and their applicability.

Forecasting Using Sample Enumeration

Of the various types of forecasting procedures, the sample enumeration procedure was adopted since it can be easily applied and requires data from only a sample of the target population. An in-depth discussion of the sample enumeration procedure and various other forecasting procedures can be found in Ben-Akiva & Lerman (1985). The nested logit model developed in section 5.3 was used to forecast the changes in the flows along the different routes in the network due to an incident on the Borman Expressway(I-94). The forecasts consist of the fraction of motorists diverting from the Borman Expressway, and the fraction of these diverted motorists who switch to the various alternate routes in the network. The forecasts were made for a range of incident durations from 5 minutes to 25 minutes. Figures 1, 2, and 3 depict the forecasts made for three different levels of information acquisition by the motorists, 10%, 50%, and 100%. The term ``Information Acquisition'' refers to the percentage of total motorists on the road who acquire advanced traffic information such as the duration of the incident, location of the incident, and traffic conditions over the network. From the forecasts we can infer that as the duration of the incident increases, the fraction of motorists diverting from the Borman Expressway also increases. However, there appears to be an overstatement towards diverting from the usual route. This is probably due to the fact that the disaggregate models were developed using SP data which could have an overstatement bias. The forecasts also indicate that a major fraction of the motorists diverting from the Borman Expressway would divert to I-90. Similar forecasts could also be made for the various levels of information acquisition and for changes in any of the explanatory variables in the models developed. The RP model for route choice, developed in section 5.2.1, can be used to forecast the effect of changes in any of the explanatory variables, especially the travel time. Table 1 shows these forecasts for changes of 10% and 20% in the travel time on I-94.

Applications of the Models

The models developed in this report can be used to forecast the changes in flows on various routes in the network. These forecasted changes are of great use to the traffic control center for providing real time adaptive traffic control over the various corridors in the network. A knowledge of the forecasted changes in traffic volumes will help the traffic controllers to provide effective signal plans on signalized arterials.

Behavioral models of route switching and route choice could also be incorporated into the framework for providing optimal information to motorists pertaining to the conditions of the network in which they are driving. Under situations of incidents, a particular redistribution of traffic in the network will provide an optimal solution and this task has to be achieved by providing the appropriate information to the drivers. In other words, the type of information to be provided will be governed by the type of response required from the drivers and this is possible only through the use of reliable behavioral models which can predict the responses of drivers under certain situations. The development of strategies for the provision of optimal information is still in the research stage and the behavioral models, such as those developed in this study, can prove to be very crucial for obtaining realistic results from simulation studies. Similar applications of the models are in studies to evaluate the benefits and cost effectiveness of providing information through Advanced Traveler Information Systems.

Table 1 Forecasts for changes in the travel time on I-94

Route Name	Existing Share	10% increase in t.time	20% increase in t.time	10% decrease in t.time	20% decrease in t.time
I-90	44.35%	58.86%	68.36%	27.36%	13.95%
US-20	1.38%	1.81%	2.3%	1.00%	0.70%
I-94	52.89%	37.42%	26.89%	70.72%	84.77%
Ridge Road	1.38%	1.91%	2.45%	0.92%	0.58%

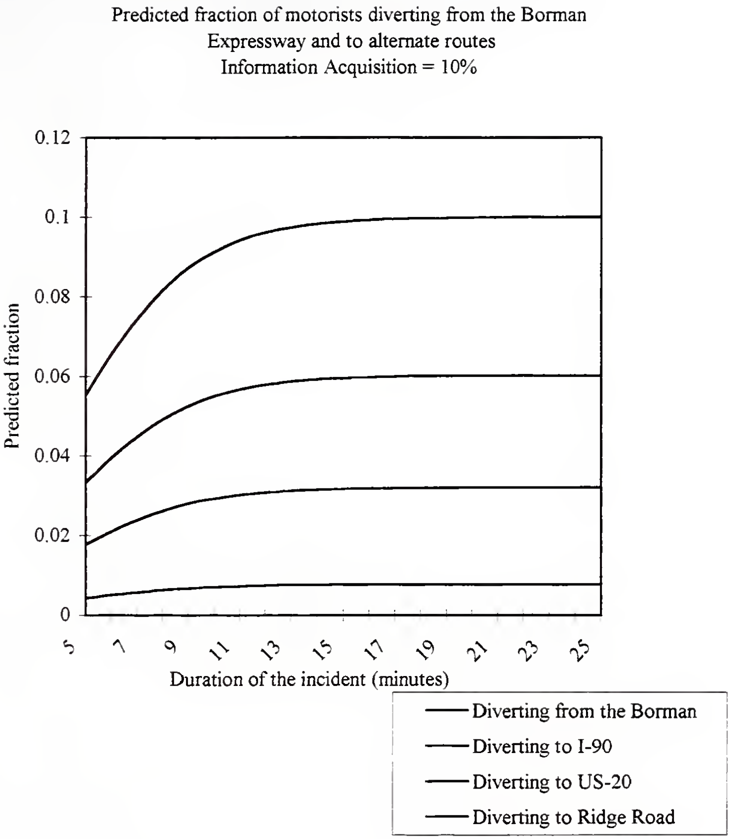

Figure 1 Forecasts Using the Nested Logit Model

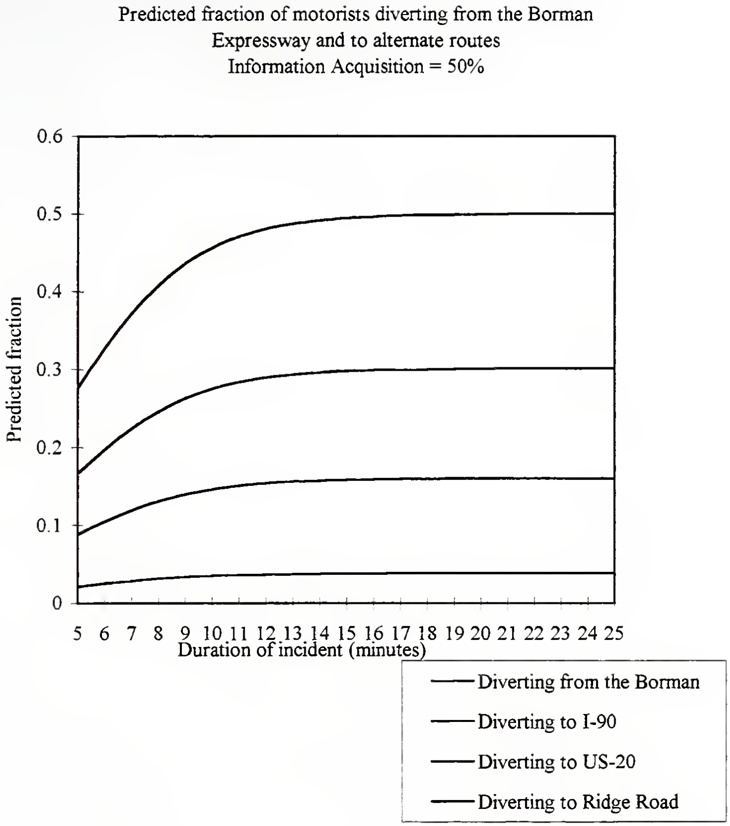

Figure 2 Forecasts Using the Nested Logit Model

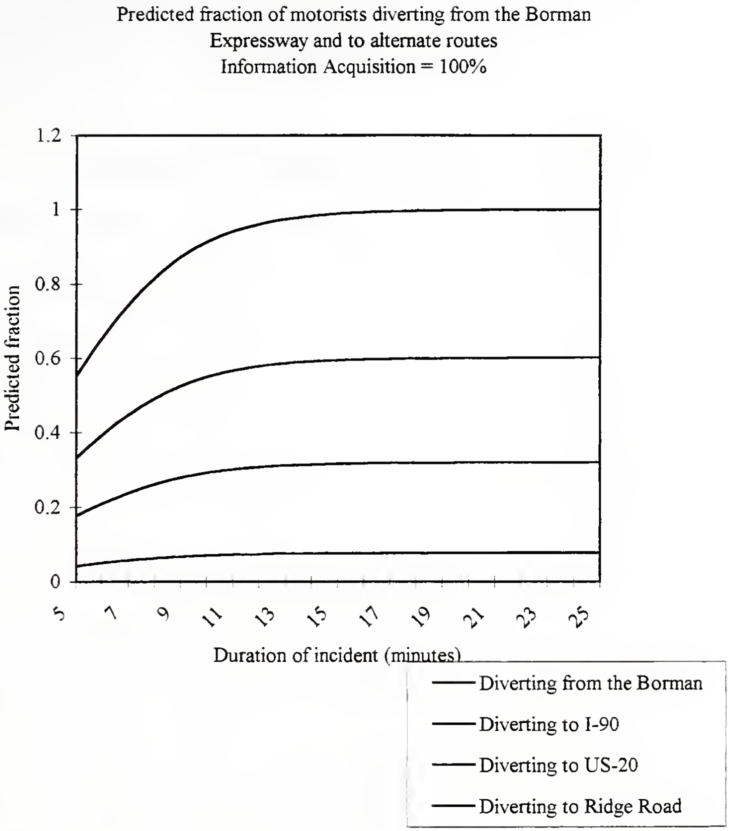

Figure 3 Forecasts Using the Nested Logit Model

CHAPTER 1

INTRODUCTION

The demand for surface transportation has been growing continually and the failure to service this demand has led to the menacing problem of congestion. This demand has however surged at an alarming rate in the recent years. Studies indicate that congestion on the roads costs the U.S nearly $100 billion every year in lost productivity. The problem of increasing demand can be tackled in two ways; one is to increase the capacity of the system and the other is the abatement of the demand itself. The latter involves measures such as congestion pricing and reorganization of the location and timing of certain human activities. However, the reduction in congestion achieved by such measures is usually more than offset by the increasing demand for travel in urban areas. Measures to improve the capacity of the system include expansion of the infrastructure or introduction of new technologies that would help utilize the existing infrastructure more efficiently. In the past, construction of new facilities to counter congestion was viewed as a feasible solution, but this is no longer a possible solution due to the nonavailability of land in urban areas and the exorbitant costs and externalities associated with such measures. Hence we have to resort to using the existing infrastructure in an efficient manner with the help of new technologies, which is exactly what the concept of Intelligent transportation System(ITS) aims at accomplishing. The main objectives of the ITS program are to improve safety, reduce congestion, and improve energy efficiency and environmental quality.

1.1 ATMS/ATIS

The Advanced Traffic Management Systems(A.T.M.S.) and the Advanced Traveler Information Systems(ATIS) are two important components of the ITS architecture. A.T.M.S. is a system that will provide traffic control and traffic management strategies in situations of recurrent and nonrecurrent congestion, which will be made possible by the use of state of the art sensors, data processing and communication devices. The early detection of incidents and predictions of incident durations will serve as inputs to the strategies for traffic control and provision of advanced traffic information to the motorists. The appropriate traffic information can then be conveyed to the motorists through the use of ATIS. In a real time control systems the responses of the motorists to the information provided to them through ATIS can be recorded in terms of the changes in link flows over the network. This information can then be fed back into the control strategy to provide the motorists with updated traffic information. The various types of mechanisms by which the traffic information could be conveyed to the motorists are; information broadcasting systems such as CMS, and HAR; pretrip information services such as Television, Radio, and other agencies providing traffic information; In-vehicle navigation systems which communicate with the traffic control center.

In the absence of any information from external sources, motorists make their route choice decisions based on their previous experiences and their limited knowledge regarding the various alternate routes. Drivers might choose routes that do not minimize their travel time or travel cost, and divert to suboptimal routes in the presence of incidents or congestion on their planned routes. In the U.S studies have indicated that excess travel accounted to 83.5 billion miles and 914,000 person-years annually which amounts to about $45 billion (King & Mast 1987). The excess miles traveled and the wrong choices made by the motorists have certain ramifications such as increased mental stress on the drivers, increased energy consumption, increased pollution, and loss of productivity. Hence Advanced Traveler Information Systems, which provide advanced traffic information to the motorists, offer an immense potential to reduce congestion and efficiently utilize the existing infrastructure.

1.2 Problem Statement

The information provided to motorists through ATIS is supplemental to the information already possessed by them by way of their own travel experiences and perceptions. Therefore, the drivers can make more informed travel related choices under the influence of such systems. However, given the same information, different drivers can be expected to behave and react in a unique fashion because the decisions of every driver are based on his/her own attitudes, preferences, and biases. Hence, in order to evaluate and estimate the effect of any kind of information provided through any particular Advanced Traveler Information System, we require user behavior models that incorporate all the factors affecting a driver's decision. These user behavior models can then be used to make reliable forecasts of traffic volumes under a given scenario. These forecasts are essential for providing real time traffic control over the network and also for updating the information provided to motorists.

1.3 Objectives of the Study

This study aims at modeling the various decisions made by motorists pertaining to the available routes, under the influence of information provided through ATIS. The different features of this study are as follows:

1. Collect revealed and stated preference data on the route choices made by motorists under the influence of information provided through Advance Traveler Information Systems.
2. Develop a binary model of route switching in the presence of incidents or congestion on their usual travel route.
3. Develop separate route choice models based on the revealed and stated preference data and then combine these two models to correct for the biases and greater noise associated with stated preference data.
4. Improve on the traditional route diversion models which consider the process of route diversion as just a switching process or a multinomial route choice process. The methodology presented in this study incorporates the correlation between the route switching process and the subsequent choice of a route, by the use of a nested model structure.

1.4 Organization of the Report

The remainder of the report is organized in the following way. Chapter 2 provides an overview of the various data collection procedures and simulators used for data collection. It also presents a comprehensive review of the various techniques used to model route choice behavior and the findings of the past research in this area. Chapter 3 details the methodologies used for the various stages of development of route choice models and the theory behind the different model formulations used in this study. Chapter 4 provides the setting of the empirical case study and elucidates the data collection procedure and discusses the results from the preliminary exploratory analysis of the collected data. Chapter 5 deals in depth with the development and understanding of the various models of route choice behavior developed in this study. Chapter 6 follows in providing an insight into the applicability and use of the models developed. Finally, chapter 7 concludes this report and provides directions for future work in this area.

CHAPTER 2

LITERATURE REVIEW

Extensive research on ATIS has focused on understanding and modeling the responses of motorists to various types of information provided to them. The data required for such analyses and modeling efforts can be categorized as 'Revealed Preference' and 'Stated Preference'. Stated Preference(SP) data relate to the behavior of motorists under hypothetical scenarios whereas Revealed Preference(RP) data relate to their behavior under real world situations. The three main sources of data are, travel surveys, driving simulators, and field experiments. Travel surveys enable the collection of both revealed preference and stated preference data. The various forms of travel surveys are mail back surveys, mutliweek diary surveys, telephone interviews, and computer aided telephone interviews. Such surveys have been used extensively and can be used to collect both stated and revealed preferences and they also provide a cheap and effective method of collecting data on various aspects of motorist behavior. However, one of the major concerns associated with travel surveys is the degree of realism that can be achieved through them while collecting stated preference data. This is because stated preference questions relate to hypothetical scenarios and they are best answered when the respondent is in that particular hypothetical environment. Creating such hypothetical scenarios is often difficult and sometimes impossible and hence a better way to achieve good responses is through the use of simulation. Driving simulators serve as an excellent tool to provide such hypothetical situations and hence have been used to collect stated preference data on driver behavior. Field experiments are a step ahead of driving simulators in the sense that they make the motorists undergo the particular situation, but they have not been widely used since they are prohibitively expensive. Following is a summary of some of the data collection efforts to study driver behavior.

2.1 Data Collection Methodologies

Mannering, Kim, Barfield & Ng (1994) distributed mail back forms to motorists on ramps leading to Interstate-5 in Seattle to collect information regarding their route choices, mode choices, departure time choices and use of traffic information. Caplice & Mahmassani (1992) used a mail survey in Austin, Texas, to collect RP data on characteristics influencing the route choice, departure time choice, and preferred arrival times at work place. Khattak, Kanafani & Le Colletter (1994) distributed mail back questionnaires to peak period commuters in the Golden Gate bridge. The survey collected RP data on the usual travel patterns, en-route/pre-trip response to certain traffic situations and other socioeconomic characteristics. Mannering (1989) conducted a telephone survey of commuters going from the suburbs to Seattle, to work. From this survey RP data was collected regarding the frequency of route and departure time changes and other socioeconomic characteristics. Jou & Mahmassani (1994) used data from a multi-week diary survey conducted in Dallas, Texas. This survey consisted of two parts; the first related to personal characteristics, commuting habits and screening questions for the second part which was a detailed diary survey. Polydoropoulou, Ben-Akiva & Kaysi (1995) used RP data from a diary survey of M.I.T commuters. Madanat, Yang & Yen (1995) used a telephone survey to collect SP data from households in Northwest Indiana. Abdel-Aty, Vaughn, Kitamura, Jovanis & Mannering (1994) performed a computer aided telephone interview of Los Angeles area commuters. Their survey is better than mail back surveys because it allows a certain degree of interaction between the respondent and the surveyor, which can help in handling a variety of situations. The following section presents a review of the different driving simulators that have been developed around the world for purposes of data collection.

2.1.1 Driving Simulators

Driving simulators have proved themselves to be invaluable for the purpose of collecting stated preference data because they create a hypothetical environment which enables the respondents to better understand the scenario and hence their responses can be expected to be more realistic. The following is a summary of the existing driving simulators. Kyoto University, Japan, developed a simulator described in Koutsopoulous, Polydoropoulou & Ben-Akiva (1993), to study the effect of past travel experiences on future pre-trip route choices. In the data collection effort using this simulator the drivers were asked to go through a series of trips and their responses and travel conditions during each trip were recorded internally. The driving task was simulated using a PC and the choices were made using the keyboard. The simulated network was very simple and consisted of one O-D pair with two route choices. The drivers were provided with traffic information and route guidance. Systems Technology, INC and JFT Associates developed a simulator, described in Koutsopoulous, Polydoropoulou & Ben-Akiva (1993), to evaluate the benefits and study the response of drivers to in vehicle navigation systems. The driving task was simulated using a slide projector, showing different views of the road, and an instrument panel. This simulator is capable of simulating and recording the responses of drivers to various types of information. The drivers are also provided information such as the occurrence of incidents, expected delay, destination arrival times, etc.. During the simulation runs the drivers were asked to minimize their trip delays and were rewarded accordingly to keep them interested in the survey. This kind of motivation, although necessary for keeping the interest of the drivers during the simulation, will not yield good representative data since the drivers will overreact and divert from their paths to save time. TNO Institute for Human Factors developed a simulator, described in Koutsopoulous, Polydoropoulou & Ben-Akiva (1993), to study human factors that affect road design, driving under poor visibility, VMS, and in vehicle navigation systems. The simulated environment consisted of mock controls such as steering wheels, pedals, instruments, etc. and a projector to display the road ahead. The simulator is capable of handling any kind of network and can provide en-route information such as congestion levels, next link to follow and can also simulate variable message signs. At the end of each run the drivers are provided with post trip information such as time taken, speed, etc.. This simulator is more realistic compared to the others in terms of simulating the driving task. The University of California, Davis, developed a simple driving simulator, described in Vaughn, Abdel-Aty, Kitamura, Jovanis, Yang, Kroll, Post & Oppy (1993), to study the pretrip route choice behavior in the presence of ATIS. The network provided by the simulator is fixed and consists of only two routes, a freeway and a side road, from the origin to the destination. The simulator does not allow the driver to switch paths en-route and this poses a very unrealistic constraint on the motorists. Traffic information on both the routes is provided to the driver, however the reliability of the information can be varied. In the simulation experiments carried out the respondents were instructed to minimize their travel time. There is a certain degree of inaccuracy associated with the responses of drivers when they are provided with an objective such as to minimize their travel time because the drivers are constrained by some objective which might not be representative of the real life scenario. In real life situations the driver might not switch routes even in the presence of information pertaining to an incident because he/she might not be familiar with alternate routes or might be a risk averse individual. The University of California, Irvine, developed a PC based simulator named FASTCARS (Freeway and Arterial Street Traffic Conflict Arousal and Resolution), described in Koutsopoulous, Polydoropoulou & Ben-Akiva (1993), to study and model the behavior of drivers under the influence of real-time traffic information. The simulator provides a view of the surrounding network, control panel information such as speed, time, etc., a roadside information viewer, and an in-vehicle navigator. The information provided to the drivers consists of maps based on their level of familiarity, VMS, next approaching exit, shortest path, HAR simulated through a voice board, and the next link to follow. Post trip scores are also provided to the driver. The simulator can handle any network and is also capable of simulating signalized intersections and incidents. Thus, this simulator is very realistic and adaptive to any scenario that needs to be evaluated. The data collection using this simulator was conducted by asking each driver to drive through the network five times, each time with a different objective. For each run the driver was required to make pre-trip and en-route travel choices which were recorded by the simulator. Three simulators - IGOR, VLADIMIR, and one developed by P.Firmin have been developed at the University of Leeds, England. The primary purpose of these was to study the factors affecting the response of drivers to information provided through ATIS. IGOR

(Interactive Guidance on Routes), described in Bonsall & Parry (1991), was developed to study how drivers comply with the information provided to them. It was also used to study how the compliance to information varies with the reliability of the advise and the past experiences. In this simulator the drivers traverse the network by making decisions at each junction in a hypothetical network. The driver is also provided with information such as the plan of each junction, route guidance, and maps. IGOR is also capable of handling any kind of network and the reliability of the advise provided can also be varied. VLADIMIR was developed to investigate the behavior of drivers under different levels of information provided and different familiarity levels. It simulates a real road network and each driver is assigned a trip purpose and a preferred arrival time. The simulation of the driving task is done by scrolling a series of digitized photographs, and what appears on the screen is the immediate vicinity of the car. Information such as speed, distance, time elapsed, link information, congestion levels, incidents, and post trip information are provided to the driver. By simulating a real road network VLADIMIR provides a better simulation environment and as a consequence better data. The University of Texas at Austin developed a simulator, described in Koutsopoulous, Polydoropoulou & Ben-Akiva (1993), to study the en-route and the pre-trip response to traffic information and the day to day changes in departure time and route choices. Their driving simulator is also connected to a traffic simulator and allows a number of users to interact with each other at the same time. Of all the users present in the network at a given time some of them are simulated internally. The users are provided information regarding the network, links and their characteristics, their position in the network, and time elapsed. The drivers go through the network, from their origin to their destination, by making pre-trip decisions and en-route decisions, at each junction, based on the information provided to them. The performance of the links is updated periodically and the network performance is based on the traffic simulation model. Incidents are modeled as a reduction in the link capacity. All types of advanced traffic information can be displayed to the user, but the reliability of the information cannot be controlled. This simulator can also be used to study the mode choice of people under a particular scenario.

The simulator used in this research was developed at M.I.T and is described in Koutsopoulous, Lotan & Yang (1994). This simulator capacitates the study of the response of drivers to various types of ATIS under different scenarios. It provides a realistic graphical user interface and provides information about the network, current link, incidents, time elapsed, direction of travel, shortest path, and the next link to follow. The amount of information to be provided can also be controlled. This simulator is explained in greater detail in chapter 3.

The simulators discussed above and other efforts to develop similar simulators have been described in greater detail in Koutsopoulous, Polydoropoulou & Ben-Akiva (1993).

2.2 Modeling Methodologies

The data collected through the different kinds of surveys and simulators, described above, have been used to model the various aspects of driver behavior. Following is a brief description of some of the modeling procedures adopted in the past. Mannering, Kim, Barfield & Ng (1994) used ordered logit/probit models for the frequency of changing routes and developed duration models for the amount of delay required to induce a route change to familiar routes. The influence of pre- trip information was modeled by ordered logit models. Khattak, Kanafani & LeColleter (1994), Bonsall & Parry (1991), and many others have used simple summary statistics to estimate the impacts of ATIS. Abdel-Aty, Kitamura & Jovanis (1995) modeled, using a binary logit model, the effect of travel time variability on route choice. Polydoropoulou, Ben-Akiva & Kaysi (1995)used binary logit models to model both pre-trip and en-route traffic information acquisition and route choice. They adopted a two stage modeling procedure that accounted for endogeneity. Vaughn, Reddy, Abdel-Aty, Kitamura & Jovanis (1995), and Vaughn, Abdel-Aty, Kitamura, Jovanis, Yang, Kroll, Post & Oppy (1993) investigated the effects of individual characteristics on travel information acquisition and use, using simple statistics and ANOVA models. They analyzed the travel decisions and accuracy perceptions using ANOVA and regression with correction for heteroscedasticity. Bonsall & Parry (1991) have also used regression techniques to model the acceptance of information provided based on the travel times which are used as a proxy for the quality of information provided. Caplice & Mahmassani (1992) used multinomial logit models for the a.m. and p.m. route switching and departure time switching propensity. Abdel-Aty, Vaughn, Kitamura, Jovanis & Mannering (1994) developed bivariate probit models to model the joint decision of whether or not commuters use their usual route and whether or not they receive traffic information. They also developed negative binomial models for the number of route changes per month based on pre-trip and en- route information. Jou & Mahmassani (1994) and Mannering (1989) used Poisson regression models for route and departure time switching. Vaughn, Abdel-Aty, Kitamura, Jovanis, Yang, Kroll, Post & Oppy (1993) modeled the sequential route choice process using binary logit with the utility functions for each alternative being updated to reflect the individual learning process. Madanat, yang & Yen (1995) used latent variables and binary logit models to study the diversion behavior of motorists. They identified the `attitude' toward route diversion and the `perception' of traffic information as two latent variables that affect the diversion behavior. Lotan & Koutsopoulous (1993) used concepts from fuzzy set theory and approximate reasoning to model route choice behavior in the presence of information. Yang, Kitamura, Jovanis, Vaughn & Abdel-Aty (1993) used Neural Networks to model the choice of motorists between the freeway and a side road. Ben-Akiva & Morikawa (1990) have proposed a methodology for modeling switching behavior using simultaneously cross-sectional RP and SP data. Their formulation exploits the advantages of both the SP and RP data and also helps overcome the disadvantages of each type of data.

2.3 Findings

The modeling efforts discussed above have led to a greater understanding of the various factors influencing travel choices such as socioeconomic factors, trip characteristics, traffic and network conditions, past experiences, etc. Following are some findings related to the various factors influencing travel behavior. Commuters with longer travel times are more likely to make changes in travel plans and these trips may have larger variances (Mannering, Kim, Barfield & Ng 1994). Males and high income commuters are unwilling to be influenced by traffic information (Mannering, Kim, Barfield & Ng 1994, Vaughn, Reddy, Abdel-Aty, Kitamura & Jovanis 1995). Commuters are more likely to use traffic information to change departure time or route, than they are to change mode

(Mannering, Kim, Barfield & Ng 1994). Route switching rate increases with provision of more complete and more prescriptive travel information (Khattak, Kanafani & Le Colletter 1994, Khattak, Polydoroupolou & Ben-Akiva 1995, Madanat, Yang & Yen 1995). Existence of diversion opportunities and knowledge of alternate routes increases route diversion propensity (Khattak, Kanafani & Le Colletter 1994). Diversion is affected by information about congestion on alternate routes (Khattak, Kanafani & Le Colletter 1994, Polydoropoulou, Ben-Akiva & Kaysi 1995). Travel time reliability and variability have an important impact on route choice behavior (Abdel-Aty, Kitamura & Jovanis 1995). Motorists under time pressure are more likely to switch routes frequently (Polydoropoulou, Ben-Akiva & Kaysi 1995). Motorists with greater tolerance to traffic delays are less likely to divert form their usual route. Drivers with a risk-taking attitude are more likely to divert due to en-route traffic information (Polydoropoulou, Ben-Akiva & Kaysi 1995). The reliability of traffic reports determines their influence on driver decisions (Polydoropoulou, Ben-Akiva & Kaysi 1995). Commuters are less likely to switch to unfamiliar routes (Khattak, Polydoropoulou & Ben-Akiva 1995). The propensity to make changes in travel decisions increases with increasing delay and the source of delay information also has a significant effect on travel decisions of motorists (Khattak, Polydoropoulou & Ben-Akiva 1995). En-route information is sought more frequently than pre- trip information (Vaughn, Reddy, Abdel-Aty, Kitamura & Jovanis 1995). The effect of pretrip information and the acquisition of en-route information are dependent on commute distance, with greater distances causing greater propensity to change route and acquire en-route information (Vaughn, Reddy, Abdel-Aty, Kitamura & Jovanis 1995). The effect of pretrip information on departure time choice and the effect of en-route information on route choice is dependent on socioeconomic characteristics information (Vaughn, Reddy, Abdel-Aty, Kitamura & Jovanis 1995). Morning and evening route switching decisions are influenced by network conditions whereas morning departure time switching is influenced by workplace and individual characteristics(lateness tolerance, preferred arrival time and job position). Traffic information has no influence on the evening departure time decision (Caplice & Mahmassani 1992). Females were found to listen more to pre-trip reports, and males were found to listen more to en-route traffic reports. The primary reason for switching routes was found to be the traffic conditions that commuters experience during their trip (Abdel-Aty, Vaughn, Kitamura, Jovanis & Mannering 1994). Commuters tend to change departure times, routes, or both more frequently in the morning than evening. The characteristics of the commuter, his/her workplace, and the traffic system, along with the commuters trip chaining patterns were found to be significant factors affecting departure time and route switching. Departure time switching occurs at a greater frequency than route switching (Jou & Mahmassani 1994). Longer commutes and congestion on commuters' usual routes cause greater route changes, congestion on their alternate route reduces the possibility of route changing, older people and married people make fewer route changes, and males change routes more frequently than females (Mannering 1989, Madanat, Yang & Yen 1995).

2.4 Discussion

From a review of the different data collection methodologies it is evident that the procedures adopted in the past result in data that are not very reliable. For example, mail back surveys have been used to collect data on stated preferences which ofcourse will lead to unreliable data. Even where simulators were used, the respondents were either university students or people who were paid to perform the surveys. These respondents are obviously not representative of the actual motorists on the road and hence any models developed using such data will be unreliable. Another shortcoming of the existing modeling efforts is the failure to recognize that the process of route diversion is not just a switching process or a multinomial route choice process. Rather, it is combination of both the above mentioned processes which needs to be modeled as a multidimensional choice process. The following chapters will elucidate these concepts.

CHAPTER 3

METHODOLOGY

The design of a model involves numerous practical and theoretical considerations, the most important and relevant to this study are discussed below. The first and foremost requirement for developing any kind of statistical or econometric model is the availability of data. The data required for model development can either be extracted from existing data bases or it needs to be collected through surveys and/or simulators. Data collection can be both an expensive and a time consuming effort. However, the quality and the type of data will eventually dictate the validity of the final models and any forecasts made using such models. Hence it is crucial to design the surveys and organize the data collection such that the data collected are reliable, unbiased and representative of the actual population in mind. But, before the survey can be carried out, there are a few preliminary steps which require careful thought and consideration. After identification and definition of the problem and the objectives, the different attributes and choice variables needed for modeling have to be identified. The kind of models that need to be developed will also influence the type of data to be collected and hence the survey has to be designed keeping in mind the models to be developed. After designing the survey, the next step is to identify the sample of the population to which the survey has to be administered, which is then followed by the actual data collection. The next step after the collection data is to summarize the data and provide descriptive statistics, which is then followed by the estimation of the model. Testing of the models is done next and finally the models are used to conduct forecasts and policy analysis. The following sections in this chapter describe the methodologies used for the different stages of this study. Section 3.1 describes the simulator used for data collection and section 3.2 describes the modeling methodology.

3.1 Data Collection methodology

In this study the data required for the development of behavioral models was not available and hence data collection was required. The data collection methodology involved the use of a driving simulator to perform the survey and record the responses of motorists. A simulator is a device which enables the participant to visualize the given situation and experience it in an artificial environment. Two aspects are of prime importance while accessing the value of a simulator. Firstly, the correspondence between the simulator and, in this case, the task of driving through a road network from an origin to a destination and secondly, the correspondence between the behavior of the participant in the real world and using the simulator. Since the purpose of this study was to understand the route choice behavior of the motorists and not to access their driving abilities, the use of a PC based simulator was deemed sufficient.

Simulators are used to simulate hypothetical scenarios and hence the data collected through them is stated preference data, but they can also be used to obtain revealed preference data. SP data collected through the use of simulators is better than mail surveys because the simulators provide an artificial environment for the experiment and consequently the subjects responses will obviously be better than that in the case of a mail survey. The data collected through simulators is free of any measurement errors since the data is recorded internally by the computer and there is no human intervention. SP data collected through simulators can also elicit some of the latent and abstract features associated with the different alternatives which determine the actual behavior. However the simulators in use today, are not without certain disadvantages. The main disadvantage with simulators is the bias involved in the responses of people. Following are some examples of biases in SP data described in Koutsopoulous, Polydoropoulou & Ben-Akiva (1993).

Prominence Hypothesis Bias: This bias is evident in situations where the subjects tend to follow the route guidance provided by the system without any thought about the reliability or accuracy of information.

Preference Inertia: This kind of bias occurs when the respondents choose to follow a particular route and stick to it in all subsequent simulation runs. Hence they exhibit an inertia toward their original choices.

Justification Bias: This bias is caused due to subjects using a particular route in trying to justify their previous choice of that route, thereby ignoring the information provided through ATIS.

Content Effect: Simulators cannot always realistically simulate all the attributes involved in alternative situations. For example, it is difficult to simulate the driving conditions during night or during inclement weather conditions even though these attributes play a major role in the choice process of an alternative. Hence the content of the survey will influence the responses of the subjects.

Effects of Incentives: When the subjects of an experiment or a survey are provided with incentives for participating in the survey, they might respond in a fashion which pleases the surveyor rather than providing realistic responses. An example of such a situation would be one in which the subjects are told to travel from an origin to a destination in the shortest time and the person with the shortest travel time is given a reward. Such a bias is evident in the study conducted by Vaughn ,Abdel-Aty, Kitamura, Jovanis, Yang, Kroll, Post & Oppy (1993).

Omission of Situational Constraints: While performing the simulations, subjects sometimes fail to consider some of the attributes which might affect their response in real life situations. Sometimes, this also results in subjects overstating their responses towards the use of new routes or facilities.

All the factors discussed above have to be considered and evaluated before deciding upon the final design of the survey and the simulator to be used so that the biases are minimized. The simulator used in this study, and described below, is quite superior in many aspects to its counterparts developed elsewhere. The simulator was developed at M.I.T by Koutsopoulous, Lotan & Yang (1994) and was further modified to suit the needs of this study. The simulator runs in a DOS environment on PCs and consists of three main modules: network performance, guidance generation, and the graphical user interface.

Network Performance: The network performance module requires as input the various spatial and operational characteristics of the network such as the link lengths, type of links, type of intersection, name of link, coordinates of each node relative to an arbitrary reference point, etc.. All this information is required to be input through an external data file, and this gives the simulator the flexibility to model any kind of network. The mean travel time on a link and the variance of travel time on that link are also required as inputs. It is however assumed that the changes in travel time on a particular link do not affect the travel time on the adjoining links. This, although a restrictive assumption, will not significantly affect the results of this study. The above assumption will affect the validity and accuracy of the information/advice given by the information system, studying the effects of which are beyond the scope of this study. The focus of this study is to understand the response of the drivers to information provided through ATIS, assuming that the information provided is accurate and reliable. During the simulation the travel time on each link is modeled as a random variable distributed about its mean. The simulator can model incidents at intersections only and the location and duration of incidents are modeled as random variables with the duration having a lower bound of 5 minutes and an upper bound of 25 minutes. Congestion in any link in the network is modeled by multiplying the travel time on the link by a factor depending on the severity of the congestion to be modeled.

Guidance Generation: The simulator is capable of generating both prescriptive and descriptive information. The amount and nature of information or guidance provided can be controlled depending on the needs of the experiment. The various types of information that can be simulated are:

- Spatial configuration of the surrounding road network with road names, current traffic levels in each link in the network, and current position of the driver in the network.
- Location and duration of incidents in the network. The incidents are indicated as bright boxes in the network. The duration of the incident can also be displayed and is constantly updated as the subject drives through the network. The incident is also cleared form the network at the end of its duration.

- Route guidance is provided to the drivers by indicating the shortest path, from their origin to destination, by a dotted line on the network. The next link to follow, on the shortest path, is also indicated to the drivers.
- Warning messages are provided to the drivers whenever there is an incident on any part of the network.

User Interface: The user interface module as shown in Figure 3.1 provides all the necessary graphics and the animation for the subjects to have a realistic driving experience. The first step in the simulation is to set all the parameters required for the simulation such as the time of day, whether incidents need to be simulated, weather conditions, etc. These parameter settings provide the flexibility to carry out different types of experiments without going into the computer code of the simulator. If the same experiment needs to be carried out for all the subjects, as done in this study, the parameter settings can be input through an external data file, saving the trouble and the time required for setting the parameters every time the simulation is run. After the parameter settings are done, the subject is asked for his/her name and initials and a separate data file is created for each respondent based on his/her initials. Each respondent then goes through a preliminary interview session before the start of the actual simulation. This preliminary survey contains questions pertaining to the socioeconomic and travel characteristics of the person. Once the parameter settings and the interview session are over, the user is presented with a schematic map of the network and is asked to choose his/her origin and destination for the trip, following which begins the driving task. The driving environment consists of three main components. The first component consists of the driving window which simulates the actual driving task. This window depicts a view of the roadway ahead as seen from behind the driving wheel. The roads are color coded to represent the level of congestion on them. For example, Gray color represents free flow traffic, Yellow represents light traffic, Green represents usual traffic, Blue represents heavy traffic, and Magenta represents bumper to bumper traffic. These color codes are also provided to the subjects as shown in Figure 3.1. On the bottom left corner of this window there is an indicator which represents the distance to the next intersection. The steering wheel is simulated by means of a small ball which moves inside a rectangular box representing the car. The subject is required to keep the, randomly moving, ball at the center of the rectangular box by using the left and right arrow keys on the keyboard. This feature of the simulator helps to maintain the concentration of the subject and keep them involved in the driving task. When the driver reaches an intersection he/she is required to choose the next link to travel on. This is done by choosing, on the keyboard, the number corresponding to that link as shown in the driving window. The second component is a window which consists of a map of the network. This map is constantly updated to show the current congestion levels on each link in the network. Incidents are indicated as bright magenta spots on the map. The current position of the driver, his origin and destination are also shown on this map. This map represents a form of ATIS and is shown on the screen depending on the parameter settings at the start of the simulation. The third component of the user interface consists of different kinds of information such as the current time, a crowfly indicating the general direction of the destination relative to the drivers' current orientation, information about the duration of the incident if any, and a message board displaying warnings about any incidents in the network. At the end of each simulation run, i.e., when the subject has reached his/her destination, he/she is provided with information regarding that trip such as the time taken to travel, a measure of safety, etc. There are a lot of data that are collected during the course of the simulation. A typical data file consists of the responses to the preliminary interview session, parameter settings, the nodes and links traversed, information about incidents, traffic levels on each link during the entire simulation, total travel time, a score of how well the subject did compared to the actual shortest path, and the degree of compliance with recommendations, if any. The use of this simulator to collect data for the purposes of this study is further explained in section 4.1.

3.2 Modeling Methodology

To understand the aggregate behavior of a certain population, one needs to first model the individual behavior. The modeling of individual behavior has to be based on a certain behavioral theory which postulates how humans behave and thereby helps in the formulation of models with parameters and variables that can be measured or estimated. Any behavioral theory is a collection of procedures that define the following elements (Ben- Akiva & Lerman 1985):

1. decision maker
2. alternatives
3. attributes of alternatives
4. decision rule

The first two components can usually be defined with the help of the scope and the nature of the study. The attributes to be considered and a suitable decision rule need to be decided by the analyst, keeping in mind the scope of the study. In this study the responses of subjects are discrete in the sense that driver either decides to divert or not divert from a particular route. To model discrete choices made by motorists, discrete choice theory has been established to be the most appropriate. Under this theory, each alternative in the choice set of an individual is associated with a certain utility and the individual is assumed to behave rationally, thereby choosing the alternative with maximum utility. The utility(U_{in}) of an alternative 'i' for an individual 'n' can be a function of the various attributes of that alternative and individual i.e.,

$$U_{in} = U(z_{in})$$

where $\mathbf{z}_{in}$ is a vector of explanatory variables of alternative 'i' for individual 'n'. An alternative $i \in C_n$, C_n being the choice set of individual 'n', is chosen if and only if

$$U_{in} > U_{jn}, \forall j \neq i, j \in C_n$$

Since we are trying to model human behavior, for which the assumption of rational behavior is reasonable, it is almost impossible to identify and measure all the explanatory variables that govern the utility of a particular alternative. Hence the random utility theory as opposed to the constant utility theory postulates that the utilities are all random variables and associates a probability with every alternative in the choice set of an individual. This can be written as follows:

$$U_{in} = V_{in} + \varepsilon_{in}$$

This means that the utility can be separated into a systematic component(V_{in}) and an error term(ε_{in}) which is a random variable. Also, the probability of an individual 'n' choosing alternative 'i' can be written as follows:

$$P_n(i/C_n) = Pr[U_{in} \geq U_{jn}, \forall j \in C_n]$$

The following sections discuss the specific discrete choice models used in this study.

3.2.1 Binary Choice Models

In the context of this study, the responses of the motorists were binary, corresponding to whether they divert or not divert from their usual route. Hence the choice set of each individual consists of only two choices. Of the various types of binary choice models available, binary logit models were used in this study. Logit models are free of any kinks or discontinuities as present in the linear probability models and furthermore, they are also computationally easier since they have a closed form solution unlike probit models. For the binary models, let us assume i and j to be the two alternatives in the choice set of each

individual. Then we can write the following:

$$U_{in} = V_{in} + \varepsilon_{in}$$

$$U_{jn} = V_{jn} + \varepsilon_{jn}$$

Hence, $P_n(i/C_n) = \Pr[U_{in} \geq U_{jn}]$

$$= \Pr[V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}]$$

$$= \Pr[V_{in} - V_{jn} \geq \varepsilon_{jn} - \varepsilon_{in}]$$

$$= \Pr[V_{in} - V_{jn} \geq \varepsilon_n] \qquad \text{where } \varepsilon_n = \varepsilon_{jn} - \varepsilon_{in}.$$

The logit model assumes that ε_n is logistically distributed, hence it has the following distribution functions:

$$f(\varepsilon_n) = \frac{\mu e^{-\mu \varepsilon_n}}{(1 + e^{-\mu \varepsilon})^2}; \mu > 0, -\infty < \varepsilon_n < \infty$$

and $F(\varepsilon_n) = \dfrac{1}{1 + e^{-\mu \varepsilon_n}}$ where μ is a positive scale parameter.

Following the above assumptions, we can write:

$$P_n(i) = \frac{1}{1+e^{-\mu(V_{in}-V_{jn})}}$$

Since μ cannot be distinguished from the parameters in the utility function, μ can be assumed to be equal to 1. Ben-Akiva & Lerman (1985) explains this model and the underlying theory in greater detail.

3.2.2 Nested Logit Model

The need for a nested model structure arises in situations where the choices are multidimensional. A multidimensional choice set could be defined as one in which each alternative in the choice set is actually a combination of two or more choices. Also, subsets of alternatives in the multidimensional choice set share some common underlying choices, which has an effect on the model assumptions. When the alternatives in a choice set are related it is possible to have certain unobserved attributes that are common to all the alternatives. This relationship between the alternatives violates the basic assumption of the multinomial logit model according to which

$$\text{cov}(U_{in}, U_{jn}) = 0$$

where \`i' and \`j' are the alternatives that share certain unobserved attributes. This violation of the multinomial model assumption gives rise to the need for a nested model structure which accounts for the common elements among subsets of alternatives. The formulation of the nested logit model is shown below.

Consider an individual with choice set C_n which can be partitioned into M subsets, represented by B_n^m, each of which share common components.

$$C_n = \bigcup_m B_n^m, \quad \text{where } B_n^m \text{ denotes the subsets}$$

The utility of an alternative in a subset B_n^m can be written as

$$U_{in} = V_{in} + \varepsilon_{in}, \forall i \in B_n^m, \ m=1,2,\ldots, M$$

The systematic utility V_{in} can be partitioned into two components; one which is common to all alternatives in that subset, and the other which is specific to each alternative. Hence,

$$V_{in} = \overline{V}_n^m + \lambda Y_{in}^m$$

where $\overline{V}_n^m$ represents the attributes that are shared by all alternatives in B_n^m. In other words, $\overline{V}_n^m$ is the mean value of the utilities in the subset B_n^m.

$$\hat{V}_n^m = E_{i \in B_n^m}[V_{in}]$$

The probability of choosing an alternative $i \in B_n^m$ is given by

$$P_n(i) = P_n(i / B_n^m) P_n(B_n^m)$$

where $P_n(i / B_n^m)$ is the conditional probability of choosing alternative $i (i \in B_n^m)$ given the subset B_n^m. This conditional probability can then be represented in the following manner:

$$P_n(i / B_n^m) = \frac{e^{Y_{in}}}{\sum_{j \in B_n^m} e^{Y_{jn}}}$$

$P_n(B_n^m)$ is the marginal probability that subset B_n^m is chosen and is expressed as follows:

$$P_n(B_n^k) = \frac{e^{\hat{V}_n^m + \lambda I_m}}{\sum_{l=1}^{M} e^{\hat{V}_n^l + \lambda I_l}}$$

where I_m represents the maximum expected utility of subset B_n^m.

$$I_m = \max[U_{jn}],\ \forall j \in B_n^m$$

$$= \log \sum_{j \in B_n^m} e^{Y_{jn}^m} \quad \text{(by property of Gumbel r.v)}$$

In the expression for $P_n(B_n^m)$ the parameter value λ associated with I_m also represents the scale of the upper level model(marginal choice model) relative to the lower level model(conditional choice model). The lower level model would have lower variance compared to the upper level model because the lower level choices form a subset of similar choices and hence there would be less variation at this level. Since the variance of the lower level model is smaller than that of the upper level model, the lower model would have a grater scale. Now, as the scale of the lower model has been set to 1, the scale of the upper level model represented by λ should be less than 1, i.e., $0 < \lambda < 1$. A rigorous mathematical derivation of the nested logit model can be found in Ben-Akiva & Lerman (1985). In this study the nested logit model was estimated using the sequential estimation procedure(LIML) described in Ben-Akiva & Lerman (1985).

3.2.3 Combining SP and RP data

Revealed Preference(RP) data are data corresponding to the behavior of people under real world situations whereas Stated Preference(SP) data correspond to the behavior of people under hypothetical situations. Stated Preference techniques have existed for a long time in the field of consumer research but started gaining ground in transport research only in the 1980's. Clearly, RP data are by far the best data in terms of the truth in the data or otherwise called the validity of the data because they reflect actual preferences of the people made in the real world. However, RP methods have certain limitations which render them unsuitable for certain studies. Some of the shortcomings associated with RP data listed below.

- RP methods cannot be used to evaluate and develop models for new facilities or events that have not been observed in the real world. Even for events that occur in the real world, it is sometimes difficult to recreate those events and to observe the behavior of people under such situations.
- In RP situations it is quite common to notice a significant correlation between the explanatory variables of intent and this reduces the efficiency of the estimates from the modeling effort, leading to biased t-statistics. A typical example of multicollinearity can be found in mode choice studies in which the travel time and the travel cost are highly correlated.
- The use of RP data also restricts the variation in the explanatory variables over which the data can be observed.
- RP methods are also susceptible to a lot of measurement errors since the attributes are not preset or specified by the surveyor. There can also be a lot of recording errors and the values of the attributes provided by the respondents are also sometimes approximate.
- RP methods cannot be adopted to measure the effects of intangible attributes on a certain choice. For example, in a mode choice study it is difficult to study the effect of abstract attributes such as comfort or attitudes of the persons towards the different modes.
- In RP situations one has no control over the dependent variable. In other words, we can observe only the choices made by the people and not their underlying preferences and/or rankings of the different alternatives available to them.

In the light of the above factors SP methods are more flexible and amenable to the researchers' needs. SP experiments are cheaper to conduct than trying to create the choice situations in the real world as would be required in order to collect RP data. SP methods can also be used to elicit multiple responses from each respondent thereby allowing for a greater amount and variety of data to be collected. SP data are however not without certain disadvantages. The responses of people under hypothetical situations are usually filled with a lot of biases. Biases such as Prominence Hypothesis bias, Preference Inertia, Policy bias, and Justification bias are not uncommon in SP data. An explanation of these biases can be found in section 3.1. It has also been found that people usually tend to overstate their preferences under hypothetical situations because there are no costs or liabilities associated with their decisions in the experiment. This overstatement might also appear due to the omission of certain situational constraints in the hypothetical environment, which in the real world would have influenced the responses of the subjects. Apart from the biases, SP data have a lot of noise associated with them. The greater noise or variation in the SP situation as compared to the RP situation is due to the fact that people respond to hypothetical situations which gives rise to a lot of uncertainty in their responses. On the contrary, it is also possible to encounter situations in which SP data have lower noise associated with them. This occurs when the respondents are too well informed about the different attributes affecting their choice and this reduces the uncertainty in their decision making. A discussion of the implications of this difference in noise in the SP models can be found in Bates (1988). The empirical case study in this report represents a situation in which the SP data is expected to have greater noise compared to the RP data. If the SP models are estimated separately without accounting for their noise, then the parameter estimates from such models cannot be compared with those from other models and the forecasts made using such models are also bound to be erroneous. To overcome these problems associated with SP models, combination of SP and RP models has been proposed and demonstrated by Ben-Akiva & Morikawa (1990). The combination of the models helps to exploit the advantages of both data types and overcome their disadvantages. Statistically speaking, the main advantages of combining SP and RP models are as follows:

- The scale of the SP model relative to the RP model can be identified.
- The biases associated with the SP data can be corrected.
- Combining both models also increases the efficiency of the parameter estimates that are common to both models.

The following section describes the procedure for jointly estimating the SP and RP models.

3.2.3.1 Framework for Combining SP and RP models

Consider a multinomial SP and RP process represented by the following models.

RP Model:

$$U_{in}^{RP} = \underline{\beta}' \underline{X}_{in}^{RP} + \underline{\alpha}' \underline{W}_{in}^{RP} + \varepsilon_{in}, \qquad i=1,2,3\ldots,C_n^{RP}$$

where U_{in}^{RP} is the utility of alternative i for observation n; $\underline{X}_{in}^{RP}$ and $\underline{W}_{in}^{RP}$ are vectors of attributes; $\underline{\beta}'$ and $\underline{\alpha}'$ are the parameters associated with them respectively. Also

$\varepsilon_{in} \sim$ i.i.d Gumbel, $\forall i \in C_n^{RP}$

and the choice is given by

$$d_{in} = \begin{cases} 1 & if\, U_{in}^{RP} > U_{jn}^{RP}, \quad \forall i \neq j \\ 0 & otherwise \end{cases}$$

SP Model: $U_{in}^{SP} = \underline{\beta}' \underline{X}_{in}^{SP} + \underline{\gamma Z}_{in}^{SP} + \upsilon_{in}$, $i=1,2,3\ldots,C_n^{SP}$

where is U_{in}^{SP} the utility of alternative i for observation n; $\underline{X}_{in}^{SP}$ and $\underline{Z}_{in}^{SP}$ are vectors of attributes; $\underline{\beta}'$ and $\underline{\gamma}'$ and are the parameters associated with them respectively. Also

$\gamma_{in} \sim$ i.i.d Gumbel, $\forall i \in C_n^{SP}$

and the choice is given by

$$d_{in} = \begin{cases} 1 & if\, U_{in}^{SP} > U_{jn}^{SP}, \quad \forall i \neq j \\ 0 & otherwise \end{cases}$$

Notice here that the systematic components of the utilities in both models have been split into two parts in order to identify the common attributes between the RP and SP process. The vector W represents the attributes that are specific only to the RP process and the vector Z represents the attributes that are specific to the SP process. This vector Z also accounts for the biases associated with the SP process. The error terms in the utilities of the SP and the RP models have been specified to be different in order to account for the difference in noise between the two processes. This difference in noise can be expressed as

$\text{var}(\varepsilon) < \text{var}(\upsilon)$

We can introduce a scaling factor μ such that $\text{var}(\varepsilon) = \mu^2\text{var}(\upsilon)$, where $\mu<1$

Since the error terms are assumed to be Gumbel distributed, it follows from the above equation that

$$\frac{1}{(scale)^2_{Rp}} = \frac{\mu^2}{(scale)^2_{Sp}}$$

$$\frac{(scale)_{Sp}}{(scale)_{Rp}} = \mu$$

We can arbitrarily normalize the scale of the RP model to 1 and hence the scale of SP model = μ (μ<1). Therefore μ represents the scale of the SP model relative to the RP model. At this juncture it is important to realize that the SP and RP models should be combined only when the responses generated by the SP and RP processes are similar. Identifying a few common variables between the SP model and a RP model is not reason enough to combine these models. By combining the two types of models we in effect restrain the common attributes to have the same parameters associated with them and this is reasonable only if both the SP and RP models represent similar choice scenarios. The various parameters of the models can be estimated by using one of two methods; Joint Estimation(Full Information Maximum Likelihood) or the Sequential Estimation Procedure(Limited Information Maximum Likelihood). In this study the LIML method was used for estimating the models and is explained below.

Step 1:

Estimate the RP model separately, identifying the parameter vectors $\hat{\beta}'^{RP}$ and $\hat{\alpha}'^{RP}$

Step 2:

Use the parameter estimates, $\hat{\beta}'^{RP}$ obtained in step 1 to calculate the fitted value of that part of the systematic utility of the SP model which is common to both the SP and RP model. In other words, calculate $\underline{\hat{V}}^{*SP}$ such that,

$$\underline{\hat{V}}^{*SP} = \underline{\hat{\beta}'}^{RP} \underline{X}_{in}^{SP}$$

Step 3:

Estimate the SP model using $\underline{\hat{V}}^{*SP}$ computed in step2. When the SP model is estimated separately without accounting for the scale parameter, the parameters estimated include the scale factor(μ) in them, i.e., the parameters estimated are $\mu\underline{\beta'}$ and $\mu\underline{\gamma'}$. By estimating the RP model in step 1 we are able to estimate $\underline{\beta'}$ and hence by using the fitted values $\underline{\hat{V}}^{*SP}$, computed in step 2, we can estimate the value of the scale parameter. The utility of the SP model incorporating $\underline{\hat{V}}^{*SP}$ is shown below.

$$U_{in}^{SP} = \mu\underline{\hat{V}}^{*SP} + \gamma\underline{Z}_{in}^{SP} + \upsilon_{in}$$

Step 4:

The purpose of the first three steps is to estimate the value of the scale parameter (μ). Once this is done we can now pool the RP and SP data together to jointly estimate the parameters. This pooling of the two data sets will increase the efficiency of the estimates. But before pooling the two data types, the attribute values of the SP data have to be scaled using the estimated value of the scale parameter $\hat{\mu}$.This scaling of the SP data accounts for the difference in scale between the SP and the RP data. The joint log likelihood function for estimating the parameters is shown below.

$$L(\alpha,\beta,\gamma) = \sum_{n=1}^{N} \sum_{i \in C_n^{RP}} d_{in}^{RP} \log\left(\frac{e^{V_{in}^{RP}}}{\sum_{i \in C_n^{RP}} e^{V_{in}^{RP}}}\right) + \sum_{n=1}^{N} \sum_{j \in C_n^{SP}} d_{jn}^{SP} \log\left(\frac{e^{V_{jn}^{*SP}}}{\sum_{j \in C_n^{SP}} e^{V_{jn}^{*SP}}}\right)$$

where $V_{jn}^{*SP} = \hat{\mu} V_{jn}^{SP}$, $\forall j \in C_n^{SP}$

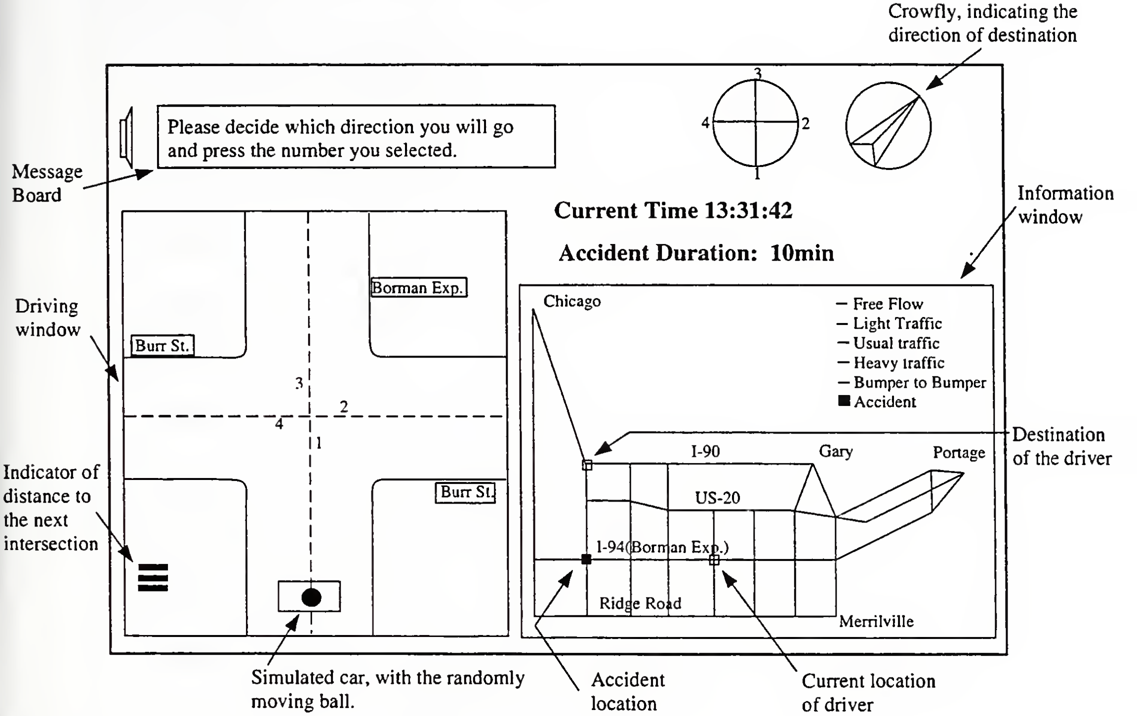

Figure 3.1 Driving Simulator

CHAPTER 4

WORK PLAN

The methodologies discussed in the previous chapter were used to study the enroute behavior of motorists in response to information provided through ATIS. This study was conducted using data from motorists in the northwestern part of Indiana. The study area consists of a sixteen mile long section of the Borman Expressway and other major roads in that region. The road network under study is shown in Figure 4.1. The Borman Expressway, which was the main corridor of interest, begins at the Indiana/Illinois state line and continues east to the Indiana toll road Interchange. The Borman Expressway and the surrounding road network experience high traffic flows. The Borman Expressway carries about 140,000 vehicles per day of which trucks constitute about 30% of the traffic volume. The heavy traffic on the Borman Expressway is associated with a high level of incidents and sometimes the involvement of trucks in the incidents increases the duration of these incidents. Even incidents of short duration, due to the heavy traffic flow, lead to heavy congestion. This congestion can be assuaged by providing advance warning to the motorists regarding the traffic conditions ahead of them. ATIS technologies such as HAR and CMS provide a means of conveying this information to the motorists. The response of the motorists to information provided through these systems will depend on the type of the information, reliability of information, and many other situational and socioeconomic factors. Hence an understanding of user behavior will enable prediction of responses for a given situation. A user behavior model which can forecast the response of motorists to a given scenario can also help in deciding the appropriate information to be broadcast.

Predicting these responses will also help in providing real time adaptive signal systems to manage flow, both on the mainline and on the arterials receiving the diverted traffic. The following section describes, in greater detail, the survey used to collect data in the study area.

4.1 Data Collection

The data collection methodology as discussed in section 3.1 was based on an interactive driving simulator. The target population for our study were the motorists on the Borman Expressway. The use of mail back surveys for such a population is not appropriate because the sampled population might not be representative of the actual population using the Borman Expressway. Another reason against the use of mail back surveys, as explained in section 3.1, is that they might lead to biased responses while collecting data on stated preferences. Hence, the best method to collect data in such cases is to approach the target population directly. In this study, since the population under study were the users of the Borman Expressway, they could not be stopped on the freeway and asked to complete a survey. However, the rest areas on the freeways serve as an excellent place to survey such motorists. Due to the above mentioned reasons, the data collection for this study was organized at the rest areas along the freeways in the study network (I-90, I-94, and I-65). The simulator was loaded on a laptop computer and taken to the rest areas and motorists using the rest areas were asked to participate in the survey. Free maps were distributed to the respondents in order to lure motorists to participate in the survey. Three to four days were spent at each rest area in order to obtain a representative sample of the actual motorists on the Borman Expressway. The following sections describe the various components of the survey.

4.1.1 Preliminary Questionnaire

The preliminary survey consisted of the following questions:

1. How familiar are you with the road network around here?
    1. Unfamiliar
    2. Not so familiar
    3. Quit familiar
    4. Very familiar
2. Purpose of your trip?
    1. Work related
    2. Shopping
    3. Recreational
3. Marital status?
    1. Married
    2. Single
4. Sex?
    1. Male
    2. Female
5. Age group?
    1. 20 and under

2. 21 - 29 yrs.

3. 30 - 39 yrs.

4. 40 - 49 yrs.

5. 50 - 59 yrs.

6. 60 and over

6. How many years have been driving?

7. Do you drive to work everyday (y/n)?

Questions regarding the socioeconomic characteristics, familiarity, and experience were included in the questionnaire since previous research has found these to be significant factors affecting travel behavior. In the next section of the survey, respondents were asked to go through a few runs on the simulator. The following three sections describe the remaining parts of the survey using the simulator.

4.1.2 Revealed Preference Scenario

For the first run on the simulator, the respondents were asked to choose their usual route through the network. The subjects were provided with a schematic map of the network and were also given full information regarding the traffic levels on every link of the network. During this run no incidents/congestion were simulated and the traffic conditions on all the links were set to the normal flow pattern in the network. This way the respondents would indicate their planned route through the network for that trip and hence the data collected would be revealed preference data.

4.1.3 Stated Preference Scenario

In the second simulation run the respondents were again asked to travel between the same Origin-Destination pair, but this time an incident/congestion was generated on their usual route chosen in the first run. The information about traffic flow on all the links and the location and duration of the incident/congestion were also provided to the users. This represented a stated preference scenario because the motorists were presented with a hypothetical incident/congestion on their usual travel route.

4.1.4 Revealed Preference Scenario

The last part of the survey involved asking the respondents to indicate, on a map, an alternate route that they would choose to go from their origin to destination. The survey was also conducted at Purdue University for a few days. The data collection effort resulted in a total of 363 observations. The required data were then extracted from the data file of each individual and placed in a single data file, compatible for use with an econometric software such as SST.

4.2 Data Summaries

The data collected from the study is summarized in Tables 4.1, 4.2, 4.3, and 4.4. Table 4.1 shows the distribution of the sample population among the various categories. Of the 363 respondents 77% were male, indicating a high percentage of males as compared to females on the Borman Expressway. The diversion rate among the males(72%) was found to be slightly higher than that of females(70%). This higher diversion rate among males could be due to the higher risk taking attitude of males when compared to females. The distribution of motorists in different age groups within the sample was quite even except for the age group of less than 20yrs who constituted 5.2% of the sample. Each of the remaining age groups constituted between 16% to 20% of the sample.

The characteristics of the trips made by the respondents using the simulator are shown in Table 4.2. The average travel time of the subjects using the simulator was 16.5 minutes on the their usual route without any incidents/congestion. The average duration of the simulated incidents was also 16.5 minutes. 46.5% of the sample population was faced with a hypothetical accident on their usual route. 77% of the people who encountered an accident on their usual route expressed a desire to divert as opposed to 67% in the case where the subjects were faced with severe congestion on their usual route. The incidents as simulated in this experiment were ones which caused total closure of traffic on that road and such incidents usually have a greater impact on the motorists in terms of their propensity to divert.

The percentage of people who switch routes under the influence of en-route information is shown in Table 4.3. Motorists in the age group of 30 to 39yrs exhibited the greatest intention to switch routes and this percentage goes down with the increasing age. This type of behavior can be expounded in the following manner. Firstly, the older people of age 50yrs and above are usually more risk averse and would not want to switch routes and go into unfamiliar territory. Secondly, these old people are usually on recreational trips (91% of the motorists of age 60 years and above indicated that they were on a recreational trip) due to which their value of time is lower and hence they would not mind waiting for a particular route to get cleared. The percentage of married people(62.8%) was found to be quite high, however no significant difference was observed between the diversion propensities of married and single people. There was a high percentage of unfamiliar people on the Borman Expressway. Most of the people were either unfamiliar or had been through the study network a few times. The motorists familiar with the network were the truck drivers and other commuters. As expected, the propensity to diver was the greatest among the motorists who were `very familiar' with the road network. This can be explained by the obvious fact that familiar drivers, knowing the network very well, would not hesitate to divert from their usual route in order to save time and stay away from the congestion. The diversion rates were very different among the remaining three groups of motorists who were not `very familiar' with the road network. The time of data collection being summer, the majority of the subjects were on a recreational trip. The motorists whose purpose of travel was work related exhibited a higher propensity to divert from their usual route. This behavior can be attributed to the fact that such people have a higher value of time as compared to people on a recreational trip and hence they would divert from their usual route to save time.

Table 4.4 shows the usual route, and the route taken by the subjects under the presence of hypothetical incidents/congestion on their usual route. Out of the 363 persons surveyed, 52.9% indicated that their usual route is through the Borman Expressway. It is also evident from this table that the two main corridors of travel, through that network, are the I-90 and I-94. US-20 and Ridge road are preferred the least since they are not freeways, meaning that they have lower speed limits, and frequent traffic lights. I-90 being a toll road attracts fewer motorists than I-94, and possibly those motorists who have a greater value of time and are willing to pay the toll. The higher diversion rate among the motorists whose usual route is through I-90(toll road) can thus be attributed to their higher

value of time. Of the 363 motorists surveyed, 71.6% indicated that they would divert from their usual route under the presence of incidents/congestion(Table 4.3). This is probably on the higher side since the subjects might have overstated their preferences in the hypothetical scenarios. The high diversion rate could also be attributed to the large amount and detail of information, such as a road map indicating location of incidents, traffic levels in each link, incident duration, etc., that were made available to the subjects. Under such situations even the risk averse and the unfamiliar motorists would consider diverting to alternate routes. Thus, the results from this study are indicative of the high potential benefits from these Advanced Traveler Information Systems. The information provided through these system can effectively intervene in the decision making process of the motorists, to attain the desired responses from the motorists. The next chapter describes the various models developed and the parameter estimates obtained using the data.

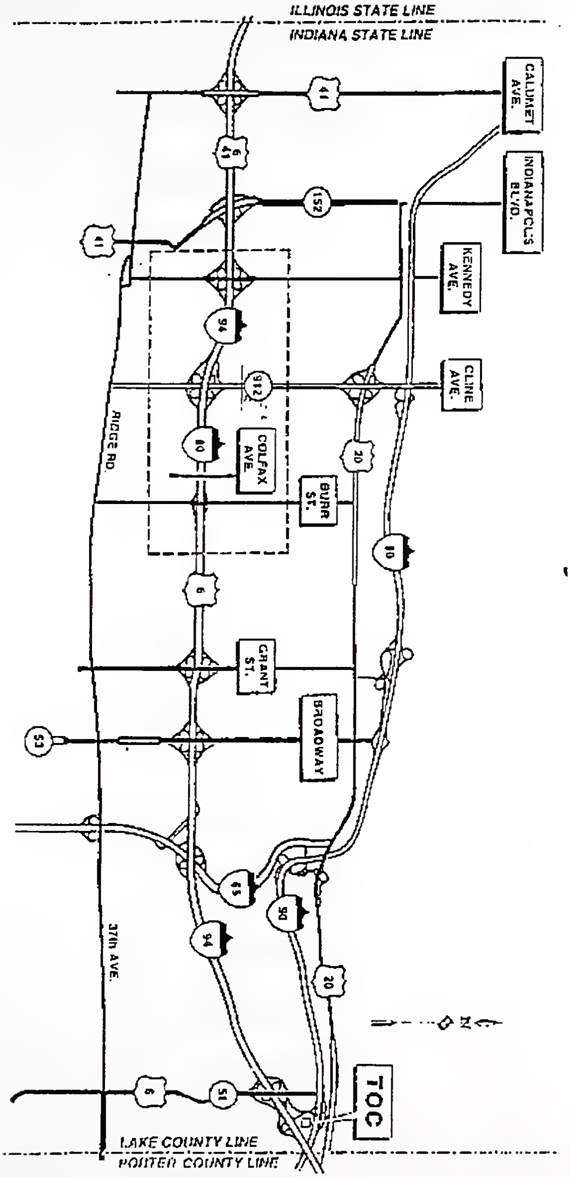

Figure 4.1 Map of the Study Network

Table 4.1 Sample Description

Attribute	% of Population
Male	77.7%
People in age group:	
< 20 yrs.	5.2%
20 - 29 yrs.	20.6%
30 - 39 yrs.	20.7%
40 - 49 yrs.	18.7%
50 - 59 yrs.	16.3%
> 60 yrs.	18.5%
Married	62.8%
Familiarity:	
Unfamiliar	32.7%
Not so familiar	34.2%
Quite familiar	22.6%
Very familiar	10.5%
Purpose of trip:	
Work related	27.8%
Recreational	72.2%
Driving experience (avg.)	25 yrs
% Who drive to work everyday	34.2%

Table 4.2 Characteristics of trips made using the simulator

Average travel time on:	
Usual route	16.5 min
Diverted route	19.9 min
People who encountered:	
incident on usual route	46.5%
congestion on usual route	53.5%
Duration of an incident (avg.)	16.5 min
No. of exits between receiving the information and incident/congestion location	4
Distance to the destination from the site of the incident/congestion (avg.)	7.5 miles
% Who divert from their usual route	71.6%
% Who return to their usual route after a diversion	16.5%

Table 4.3 Diversion characteristics of the sample population

Attribute	% Diverting
Males	71.9%
Females	70.3%
Age group:	
< 20yrs.	78.9%
20 - 29 yrs.	77.3%
30 - 39 yrs.	81.3%
40 - 49 yrs.	67.6%
50 - 59 yrs.	67.8%
>60yrs.	59.7%
Married	71.5%
Single	71.8%
Familiarity level:	
Unfamiliar	65.5%
Not so familiar	73.4%
Quite Familiar	69.5%
Very Familiar	89.5%
Purpose of trip:	
Work related	78.2%
Recreational	69.1%
Motorists faced with incidents on their usual route	77.0%
Motorists faced with congestion on their usual route	67.0%

Table 4.4 Route choice statistics of the sample

Usual Route	% Usage	% Diverting	% Diverting to	
I-90(Toll Road)	44.3%	75.2%	US-20	38.8%
			I-94	58.7%
			Ridge Road	2.5%
I-94(Borman)	52.9%	54.7%	US-20	35.2%
			I-90	64.8%
			Ridge Road	0%
US-20	1.4%	100%	I-94	100%
			I-90	0%
			Ridge Road	0%
Ridge Road	1.4%	60%	I-90	0%
			US-20	0%
			I-94	100%

CHAPTER 5

DATA ANALYSIS & MODEL DEVELOPMENT

This chapter deals with the development of the various models in this study. The three models developed are a binary route switching model, a combined SP and RP model, and a nested logit model of route diversion and choice. A detailed discussion of the various parameter estimates is also presented for every model. The various explanatory variables that were used to model the decisions of the motorists are described below.

sex: A dummy variable indicating the sex of the person

= 1 if male

2 if female

old: A dummy variable indicating the age of the person. It is specified as shown below.

= 1 if age $\geq$ 40 yr.

0 if age < 40 yr.

mar: A variable indicating the marital status of the person.

mar = 1 if married

0 if single

fam: fam1, fam2, fam3 are dummy variables indicating the familiarity of the motorist with the surrounding road network. fam1, fam2, fam3 represent each of the three levels of familiarity namely, `very familiar', `quite familiar', and `not so familiar' respectively. The familiarity level of `unfamiliar' was assumed the base familiarity level in the model. These dummy variables take a value equal to one if the motorist possesses that level of familiarity and a value zero otherwise.

purp: purp2, purp3 are two dummy variables indicating the purpose of the trip.

purp2 and purp3 represent the purposes namely, `shopping', and `recreational' trips respectively. These dummy variables take a value one if the purpose of the motorist corresponds to what that variable represents and zero otherwise.

expe: This variable indicates the driving experience of the person.

dtw: This is a dummy variable indicating whether the person drives to his work place everyday.

dtw = 1 if he/she drives to work everyday

0 if he/she does not drive to work everyday

time: This variable represents the difference in the travel time between usual and the alternate routes of the motorist, in the presence of incidents/congestion on he usual route. This variable can be defined as follows:

time = travel time on the usual route + delay due to incidents/congestion

- travel time on the alternate route

aorc: This is a dummy variable indicating whether there was an accident or high congestion on the usual route of the motorist.

aorc = 1 if there was an accident on the usual route

0 otherwise

dur: Indicates the duration of the incident on the usual route of the person.

opp: Represents the number of opportunities available to the motorist to divert from his/her usual route. In other words, it is the number of exits on the freeway between the point of receiving the information about the incident/congestion and the actual location of the incident/congestion.

dist: This variable represents the distance of the site of the incident/congestion from the destination of the motorist.

Socioeconomic variables such as sex, age, driving experience were included in the model since they have been shown to significantly affect driver behavior. Females and older drivers are known to be risk averse and hence it expected that they exhibit lower diversion propensities. The familiarity of the drivers with the surrounding road network could be a significant factor since familiar drivers would not hesitate to divert from their usual routes to save time and avoid congestion. The purpose of the trip can play a significant role in route diversion because motorists on a recreational trip have a lower value of time when compared to motorists on a work related trip and hence they would be willing to tolerate greater delays. The variable `time', which represents the difference in the travel time between the usual and the alternate routes, is very important and plays a decisive role in en-route choice decisions made by the motorists. This estimate of delay is something that the motorists can easily perceive and they have this in mind while having to make route choices. The accidents simulated in this study were the ones that would cause a total blockage of all the lanes on the freeway, and in the case of congestion, the traffic would still keep moving, but at a very slow speed. Motorists usually prefer to keep moving slowly on a congested freeway instead of having to stop on the freeway for an accident to get cleared, hence it is possible that motorists have different diversion propensities when faced with accidents as opposed to congestion. The duration of the incident will obviously affect the diversion propensities with longer incident durations leading to a greater diversion propensity. The variables such as `opp' and `dist' that relate to the site of the incident/congestion relative to the position of the driver and his/her destination can also play a role in the decision process. When the motorists have many opportunities to divert, which means that they are quite far from the site of the incident, they may continue on their usual route and hope for the incident to get cleared by the time they reach it. Therefore it is expected that as the opportunities to divert increase, the propensity to divert should decrease. Similarly, as the motorists approach their destination, they are usually more impatient to get there and are likely to take a diversion from their usual route in the presence of incident/congestion. The variables such as `time', `opp', and `dist' have never been investigated before in such studies and incorporating such effects in the models should serve to increase their validity.

5.1 Binary Choice Model

The dependent binary choice variable used in this model can be defined as follows:

$$y_n = \begin{cases} 1 & \textit{if he / she diverts from the usual route} \\ 0 & \textit{if he / she does not divert from the usual route} \end{cases}$$

The specification of the systematic utilities in the preliminary binary logit model is shown below.

$$\begin{aligned}V_{in} = \beta_0(1) + \beta_1(sex) + \beta_2(old) + \beta_3(mar) + \beta_4(fam1) + \beta_5(fam2)\\ + \beta_6(fam3) + \beta_7(purp2) + \beta_8(purp3) + \beta_9(\exp e) + \beta_{10}(dtw)\\ + \beta_{11}(time) + \beta_{12}(aorc) + \beta_{13}(dur) + \beta_{14}(opp) + \beta_{15}(dist)\end{aligned}$$
$$V_{jn} = 0$$

where,

V_{in} = systematic component of the utility of diverting from the usual route

V_{jn} = systematic component of the utility of not diverting from the usual route

The maximum likelihood procedure as described in Ben-Akiva & Lerman (1985) was used to estimate the parameters of the model. The software SST (Dubin & Rivers 1988) was used throughout this study to estimate the parameters and perform other statistical tests.

An initial examination of the correlation coefficients between the explanatory variables did not reveal any significant correlations between any of the variables, thereby eliminating the fear of any serious problems of multicollinearity. The parameter estimates of the preliminary model are shown in Table 5.1. As is seen from this table, almost all of the socioeconomic variables turned out to be statistically insignificant. On the other hand, the variables such as time, dur, opp, and dist were highly significant. This conforms to our prior intuition regarding the significance of such variables in the choice process. The ρ^2 value of the model was 0.577 indicating a good fit. Most of the statistically insignificant variables were removed from the preliminary model to arrive at the model shown in Table 5.2. The likelihood ratio test was also performed on the model in Table 5.1 to test the following hypothesis:

$$\begin{aligned}H_0:&\quad \beta_1 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{12} = 0\\ H_1:&\quad \text{not all } \beta\text{'s} = 0\end{aligned}$$

Where the β's are the parameters associated with the different variables as shown in the systematic utilities. The likelihood ratio test statistic corresponding to the above hypothesis is

$$-2(L^R - L^U) \sim \chi^2_{d.f(R)-d.f(U)}$$

$$\Rightarrow -2(-112.4 + 106.44) = 11.48 < \chi^2_{10,0.05}(18.31)$$

Hence we can accept the null hypothesis H_o. The t-statistics associated with the variables in Table 5.2 indicate that all of them are highly significant. The variables such as `time', `dur', `opp', `dist' were tested for any nonlinear effects that they might have on the dependent variable. This was done by the power series expansion approach Ben-Akiva & Lerman (1985) in which each of the variables was represented in a polynomial form of the second degree. The goodness of fit $\overline{\rho}^2$, t-tests and likelihood ratio tests were used to test the statistical significance of these nonlinear forms. The only nonlinear specification that was statistically significant was that for the variable `opp'. Hence the variable opp^2 was included in the model as shown in Table 5.3

Once the different variables that went into the model were determined , the next step was to conduct the market segmentation tests. The market segmentation tests were conducted based on the socioeconomic variables such as familiarity, sex, marital status, and age. The tests based on these variables did not reveal any significant differences between the corresponding market segments. The sample was also segmented based on whether the motorists were faced with incidents or congestion on their usual route. This was done to detect any differences in the behavior of motorists under the influence of incidents or high congestion levels. The χ^2 test proved that there was a significant statistical difference between the two market segments. t-tests were also conducted to investigate the difference between the corresponding variables of the two market segments. It was found that the parameter associated with the variable opp^2 was statistically different between the two market segments. This difference between the two market segments was incorporated into the model by replacing the variable opp^2 with two variables, $aopp^2$ and $copp^2$ corresponding to situations of accidents and congestion respectively.

The final model is shown in Table 5.4. The estimated values of the parameters in the final model are discussed below. The alternative specific constant, specific to the `divert' alternative, had a positive value indicating that, everything else being a constant, the motorists would prefer to divert from their usual route under the influence of an incident/congestion. Other modeling efforts in this area by Polydoropoulou, Ben-Akiva & Kaysi (1995) and Khattak, Polydoropoulou & Ben-Akiva (1995) have indicated that the motorists, under real world conditions, are usually not inclined towards diverting from their usual route. The positive value of the alternative specific constant in our model could be attributed to two reasons. First, the data used for the model development are stated preference data, as opposed to revealed preference data used by Polydoropoulou, Ben-Akiva & Kaysi (1995) and Khattak, Polydoropoulou & Ben-Akiva (1995), and under such hypothetical situations the subjects tend to overstate their responses. Thus, some of the subjects would divert from their usual route even if in real world conditions they actually would not. Secondly, in the simulation study, the motorists were provided with substantial descriptive information such as a detailed road map, traffic flow conditions in the network, location of incidents, duration of accidents, and their current position in the network. Under the presence of such information even the unfamiliar and the risk averse motorists might be willing to divert from their usual route. The parameter associated with the variable `old' had a negative value indicating that, everything else being a constant, older people have a lower propensity to divert from their usual route. This result conforms to our prior intuition and also corroborates the results from similar studies (Mannering 1989). The variable `time', representing the difference in travel times between the usual and the alternate route, had a positive coefficient. This implies that, everything else being a constant, as the travel time on the usual route increases relative to the alternate route, the propensity to divert increases. This result is perfectly intuitive since the motorists would be more inclined to divert as the travel time on their usual route increases. The parameter associated with the variable `dur' had a positive sign that was both intuitive and conformed to our prior expectation. The variables $aopp^2$ and $copp^2$ had negative parameter estimates implying that, everything else being a constant, as the number of opportunities to divert increase, the propensity to divert decreases in a nonlinear fashion. This behavior can be explained in the following manner. As the number of opportunities to divert increase, the distance of the motorists from the site of the incident increases; hence, the motorists are likely to continue on their usual route hoping that the accident would get cleared by the time they reach the site of the accident. The coefficient of opp^2 specific to the class of people who encountered an accident was lower than that for the class of people who encountered a high level of congestion on their usual route. This implies that, as the number of opportunities to divert increase, the propensity to divert is greater when the motorists are faced with congestion rather than an accident on their usual route. The justification for such a behavior could be that the accident congestion is usually of shorter duration than the congestion caused due work zones etc., and hence, when encountered with an accident the motorists might continue on their usual route hoping that the accident would get cleared by the time they reach the site of the accident. The variable `dist' had a negative coefficient indicating that as the distance between the site of the incident and the destination decreases, the propensity to divert increases. This behavior is intuitive because as motorists get closer to their destination they become more impatient to get there and hence their propensity to divert from their usual route increases.

5.2 Models with combined SP and RP data

As discussed in the methodology (section 3.2.3), by combining SP and RP data we can correct for the biases in the SP data, establish the scale of the SP models, and obtain more efficient estimates. In this case study SP and RP data relating to the choice of a route were available. The RP data correspond to the choice of a route by the motorists under normal traffic conditions and the SP data correspond to the choice of a route under the condition of incidents/congestion on the usual travel route. Since the RP and SP situations represent similar choice processes, it is meaningful to combine the two data types to develop more accurate SP models. The RP, SP and the joint models are discussed in the following sections.

5.2.1 RP Model

The RP model was developed by using the usual route followed by motorists as their chosen alternative out of a set of four possible routes. The choice set of every individual was assumed to consist of four possible routes namely, I-90, US-20, and Ridge

Road. These four routes constitute the main corridors for east-west traffic in the study network and hence were used as an approximation for the total choice set of every motorist. The above assumption might lead to some biases in the models if the choice set of the motorists differ significantly from the assumed choice set. However, the approximation made in this study is reasonable in the light of the difficulty in obtaining responses from people regarding all the routes in their choice set. The choice of a route can thus be modeled using a multinomial logit model.

The multinomial logit model is shown in Table 5.5. In this table the route names within the brackets, juxtaposed to the variable names, indicate the route to which the variables are specific to. The parameters associated with the travel times on all four routes were highly significant and negative meaning that as the travel time increases the utility decreases. Since only the travel times on the usual and the alternative routes were available, the travel times on the remaining two routes were assumed to be equal to the travel time on the alternate route. Males had the greatest utility associated with I-90 followed by I-94, US-20, and Ridge Road in decreasing order. The preference of males towards the freeways could be because they are more aggressive and impatient and hence would prefer the freeways as compared to the state roads which are slower. For people who were very familiar with the road network the model shows that they prefer Ridge Road the most. This behavior is meaningful because the people who are familiar with the road network would not hesitate to take the state roads, whereas the unfamiliar people would prefer the freeways more than the state roads to avoid getting lost. For motorists whose final destination was Chicago, I-90 was found to have the maximum utility followed by I-94, US-20, and Ridge Road in decreasing order. I-90 would obviously the best route to take to go into Chicago since it leads straight into downtown Chicago. The ρ^2 value of the model was 0.58 indicating a very good fit to the data.

5.2.2 SP Model

The SP model corresponds to the choice of a route in the presence of an incident/congestion on the usual route of the motorist. The multinomial logit model developed for the SP data is shown in Table 5.6. In this model the parameters associated with the travel times on the two freeways had a negative sign whereas those associated with the state roads had positive sign. The positive signs of the travel time coefficients could represent a bias in the SP data which can possibly be corrected by combining the SP model with the RP model. Under the presence of incidents on their usual routes, motorists who were very familiar with the road network were found to prefer the freeways to the state roads. This behavior is contradictory to what was observed in the RP model and hence this could be another bias in the SP data. As the experience of the motorists increases the utility of I-94 increases and this is meaningful since experienced drivers would prefer to stay on the freeways in the presence of incidents/congestion because these are usually cleared faster than the state and other local roads. Just as in the case of the RP model, the motorists going to Chicago were found to have a greater utility associated with I-90. However, when compared to the RP model, the motorists seem to have overstated their use of I-90 if their destination were Chicago. Motorists whose destination was not Chicago and were headed west into Illinois were found to have the greatest utility associated with I-94 which is very meaningful since this freeway avoids the downtown Chicago area.

5.2.3 Combined SP and RP model

Comparing the RP and SP models in Tables 5.5 and 5.6 respectively it is possible to identify a few common variables between them such as the alternative specific variables, travel times, familiarity, and the destination variables. The sequential estimation procedure explained in section 3.2.3.1 was used to jointly estimate both the models. The scale parameter μ which represents the scale of SP model relative to the RP model was found to be equal to 0.1537 and was also highly significant at the 95% confidence level. The value of $\hat{\mu}$ is reasonable since it lies between 0 and 1. This also confirms our prior expectation that the SP data has greater variance and noise compared to the RP data. Comparing the parameter estimates of the common variables between the two models, it can be seen that some of the parameters of the SP model are smaller than those of the RP model. This is because when the SP and RP models are estimated separately, the parameter estimates of the SP model are actually estimates of $\mu\beta$ since the scale of the SP model has not been accounted for. As the value of μ is less than unity, the lower values of the SP parameters can be explained.

The parameters of the combined model are shown in Table 5.7. The dummy variables were all positive, indicating that I-94 is the most attractive route followed by I-90, US-20 and Ridge Road. These parameters are meaningful since the freeways are obviously more attractive than the state roads, and among the freeways, I-90 being a toll road it would be preferred less than I-94. The travel time coefficients were all highly significant, and negative indicating that as the travel time increases the utility of that route decrease. No statistical difference was found between the parameters associated with the travel times on the four routes, which was confirmed by a likelihood ratio test. Thus, by combining both data types it was possible to correct for the positive travel time coefficients obtained in the SP model. Also, the statistical significance of the parameters in the combined model was found to be greater than in the separate models. This is a result of the increase in efficiency achieved by combining both data types. As in the case of the RP model, motorists who were very familiar with the road network were found to have the greatest utility associated with Ridge Road. If the destination of the motorist was Chicago then the freeways were found to have a greater utility than the state roads and I-90 was found to have the greatest utility. These results are similar to those obtained in separate SP and RP models, and are also very meaningful. The bias caused due to the overstatement to use I-90 which was observed in the SP model was also corrected for in the combined model. Hence, by combining the two types of data, the parameter estimates were more meaningful and it also helped in correcting for some of the biases in the SP data. Combining the two models also enabled the identification of the scale parameter and increased efficiency of the estimates.

5.3 Nested Logit Model

Traditionally, route diversion has been modeled as a switching process involving the decision to switch or not to switch from the usual route. Modeling route diversion as just a switching process is not appropriate because in reality the process of diverting from the usual route involves two distinct yet related choices. The two choices that contribute to the process of diversion are the choice of whether to switch or not to switch from the current route and if switch, to which alternate route to switch to. These two choices constitute a multidimensional choice set in which a subset of the choices are correlated with each other. Hence the route diversion process can be represented appropriately by a nested logit model. The proposed nested model structure is shown in Figure 5.1. In this figure, the route choice process occupies the lower level and the route switching process occupies the upper level. The choice set of every individual was assumed to consist of four possible routes namely, I-90, I-80, US-20, and Ridge Road. These are the main routes for east-west traffic in the study corridor and hence are a good approximation for the choice set for a motorist. However, information regarding the travel time was available only for two of these routes: the usual route of the motorist and one alternate route. Obtaining information pertaining to all the routes in the choice set of an individual is a difficult task since it would increase the time needed to complete the survey. Moreover, people are usually not aware of the travel times on all their alternate routes. Hence, it was assumed that the travel times on all the alternate routes are the same. The following sections explain the specification of the nested logit model.

5.3.1 Lower Level Model

The lower level model is a conditional choice model representing the choice of a route to which the driver would divert to, given that he/she diverts from his/her usual route. The motorist chooses one of the four routes as his usual route and hence when he/she decides to divert to another route, his/her choice set would consist of the three remaining routes. The specification of the systematic utilities of the alternatives in the multinomial logit model, constituting the lower level, are shown below.

$$V_{I\text{-}90} = \beta_1 + \beta_6(vfam) + \beta_8(Chicago) + \beta_9(west) \qquad [5.1]$$

$$V_{US-20} = \beta_2 + \beta_7(vfam) + \beta_{10}(west) \qquad [5.2]$$

$$V_{I-94} = \beta_3 + \beta_4(female) + \beta_5(old) \qquad [5.3]$$

All the above utilities are specified assuming Ridge Road to be the base. Notice here that travel time on the routes is not included in the specification. This, as explained before, is due to the fact that only the travel time on one of the three routes was known, and was assumed to be the same for the remaining alternate routes. This assumption prevents the estimation of the parameter associated with travel time.

The estimated multinomial logit model is shown in Table 5.8. The alternative specific constants are all highly significant and positive indicating that Ridge Road is the least preferred route. Since there are other dummy variables in the model, the alternative specific constants can not be interpreted in isolation from these dummy variables. The parameter associated with the variable `female' specific to I-94 was positive indicating that under situations of incidents, females prefer to stay on the freeway. This can be attributed to the risk averseness of females compared to males. Older drivers had a greater preference towards I-94 which is a freeway, and this could be explained by the risk averse nature of older motorists. The parameter associated with the dummy variable `Vfam' was negative and when added to the alternative specific constants indicated that drivers who were very familiar with the road network would prefer to divert to I-80. They also suggest that very familiar drivers would prefer the state roads to I-90. This result is meaningful since I-90 is a toll road and would therefore be less attractive compared to I-80 and the other state roads. For motorists whose destination was Chicago, I-90 had the maximum utility which is again a meaningful result because I-90 leads directly into downtown

Chicago. Motorists whose destination was not Chicago and were headed west into Illinois had the highest utility associated with I-80 followed by Ridge Road, I-90 and US-20. I-80 is the major freeway that continues west and hence would be the most attractive route to choose.

5.3.2 Upper Level Model

The upper level model consists of a switching binary logit model. This switching model is a marginal choice model which represents the choice of a driver to divert or not from his/her usual route under the conditions of incidents/congestion on the usual route. The systematic utility of the `divert' alternative is shown below, assuming the `not divert' alternative to be the base.

$$\begin{aligned} V_{divert} = {} & \alpha_0 + \alpha_1(old) + \alpha_2(purpose\_work) + \alpha_3(duration) \\ & + \alpha_4(aopp^2) + \alpha_5(copp^2) + \alpha_6(distance) + \mu(I_{divert}) \end{aligned} \qquad [5.4]$$

where,

I_{divert} = inclusive value of lower level alternatives

= $\max[U_{jn}]$, j=1,2,3

= $\ln\sum_{j=1}^{3} e^{V_{jn}}$ [5.5]

In equation 5.5, V_{jn} is the systematic utility of route `j' for individual `n' in the lower level model. As explained in section 4.2.1, the utility associated with the alternate routes should include the travel time variable. Hence, we can write the systematic utilities of the alternatives in the lower level model as following:

$$V_{jn} = V^*_{jn} + \beta_t(tt), \qquad j = 1,2,3 \qquad [5.6]$$

where V_{jn}^{*} is the systematic utility of a route as estimated using the lower level model specification and `tt' denotes travel time. From equations 5.5 and 5.6, we have:

$$
\begin{aligned}
I_{divert} &= \ln \sum_{j=1}^{3} e^{V_{jn}^{*}+\beta_t(tt)} \\
&= \beta_t(tt) + \ln \sum_{j=1}^{3} e^{V_{jn}^{*}} \\
&= \beta_t(tt) + I_{divert}^{*} \qquad [5.7]
\end{aligned}
$$

Substituting equation 5.7 in equation 5.4, we obtain

$$
\begin{aligned}
V_{divert} = {} & \alpha_0 + \alpha_1(old) + \alpha_2(purpose\_work) + \alpha_3(duration) \\
& + \alpha_4(aopp^2) + \alpha_5(copp^2) + \alpha_6(distance) \qquad [5.8] \\
& + \mu(\beta_t(tt) + I_{divert}^{*})
\end{aligned}
$$

We can estimate sequentially the value of I_{divert}^{*} using the lower level model, and use this estimated value in equation 5.8 to estimate the parameters of the upper level model. The appropriateness of the nested logit model structure, shown in Figure 5.1, will be judged by the statistical significance of the coefficients of both the variables, travel time, and I_{divert}^{*} ($\mu\beta_t$ and μ respectively). The estimated value of the parameter μ will indicate the ratio of the scale of the upper level model to the lower level model.

The estimated upper level model is shown in Table 5.9. In this model, the choice of not diverting from the usual route was assumed as the base case. Older drivers have less propensity than younger drivers for diverting: older drivers tend to be more risk averse than younger drivers. Motorists whose purpose of travel was work related were found to have a greater propensity to divert than motorists who were on a recreational trip; this result is intuitive since commuters have a higher value of time. The parameter associated with the duration of the incident was positive, indicating that as the duration increases, the utility of diverting also increases which is intuitive. The variables $aopp^2$ and $copp^2$ had negative parameter estimates implying that, as the number of opportunities to divert increase, the propensity to divert decreases in a nonlinear fashion. This result can be explained in the following manner: as the number of opportunities to divert increases, the drivers are likely to continue on their usual route hoping that the incident would clear by the time they reach the site of the incident. The variable `dist' had a negative coefficient indicating that as the distance between the site of the incident and the destination decreases, the propensity to divert increases. This may be due to drivers becoming more impatient as they get closer to their destination or to increased familiarity with the road network closer to their destination. The variable `time' had a positive coefficient implying that as the travel time on the usual route increases relative to the alternate route, the propensity to divert increases. The variable $\hat{I}^*_{divert}$, was not found to be statistically significant. However, as explained in section 4.2.2, the inclusive value of the lower level choice process consists of both the variables, `time' and $\hat{I}^*_{divert}$. Since the variable `time' was highly significant, we can conclude that the inclusive value is significant. This implies that the use of a nested logit model for the process of route diversion is appropriate. The estimated value of the coefficient μ associated with $\hat{I}^*_{divert}$ was also found to be in the acceptable range of 0 to 1, meaning that the lower level choice process has lower noise compared to the upper level. Hence, the choice structure assumed, and depicted in Figure 5.1, is appropriate.

Table 5. 1 Estimation results for the preliminary binary logit model

Independent Variable	Estimated Coefficient	t-statistic
one	4.841	3.258
sex	-0.130	-0.301
old	-0.730	-1.248
mar	-0.170	-0.416
fam1	-1.406	-1.630
fam2	-0.562	-0.659
fam3	-1.317	-1.505
purp2	-1.342	-1.792
purp3	-0.680	-1.551
expe	-0.009	-0.481
dtw	-0.120	-0.315
time	0.574	8.311
aorc	0.018	0.017
dur	0.305	3.864
opp	-0.364	-3.807
dist	-0.155	-3.043

Summary Statistics

No. of observations = 363 (0) = -251.6 ($\hat{\beta}$) = -106.44

$\rho^2 = 0.57$ $\bar{\rho}^2 = .513$

Table 5.2 Estimation results for the improved binary logit model

Independent Variable	Estimated Coefficient	t-statistic
one	2.675	4.003
old	-0.830	-2.405
time	0.577	8.469
dur	0.297	7.401
opp	-0.355	-3.996
dist	-0.157	-3.264

Summary Statistics

No. of observations = 363 (0) = -251.61 $(\hat{\beta}) = -112.14$

$\rho^2 = 0.554$ $\bar{\rho}^2 = .531$

Table 5.3 Estimation results for the binary logit model incorporating the nonlinear effects of certain variables

Independent Variable	Estimated Coefficient	t-statistic
one	2.199	3.968
old	-0.846	-2.436
time	0.580	8.425
dur	0.291	7.253
opp^2	-0.403	-4.224
dist	-0.161	-3.358

Summary Statistics

No. of observations = 363 $\quad$ L(0) = -251.61 $\quad$ $L(\hat{\beta}) = -111.04$

$\rho^2 = 0.559$ $\quad$ $\bar{\rho}^2 = 0.535$

Table 5.4 Estimation results for the final binary logit model

Independent variable	Estimated Coefficient	t-statistic
one	1.815	3.191
old	-0.872	-2.464
time	0.638	8.186
dur	0.415	6.586
$aopp^2$	-0.092	-4.628
$copp^2$	-0.028	-2.758
dist	-0.145	-2.969

Summary Statistics

No. of observations = 363 $L(0) = -251.6$ $L(\hat{\beta}) = -105.23$

$\rho^2 = 0.582$ $\bar{\rho}^2 = 0.554$

Table 5.5 RP model estimated separately

Independent Variable	Estimated Coefficient	t-statistic
Dummy(I-90)	0.671	0.323
Dummy(US-20)	2.331	1.037
Dummy(I-94)	1.173	0.582
Time(I-90)	-0.612	-6.718
Time(US-20)	-0.728	-4.569
Time(I-94)	-0.546	-3.665
Time(Ridge Rd.)	-0.602	-3.665
Male(I-90)	2.097	2.644
Male(I-94)	1.444	1.894
Vfam(Ridge Rd.)	2.076	2.064
Chicago(I-90)	2.894	2.242
Chicago(I-94)	2.279	1.782

Summary Statistics

No. of observations = 363

$L(0) = -503.2$ $L(\hat{\beta}) = -211.35$

$\rho^2 = 0.58$ $\bar{\rho}^2 = 0.556$

Table 5.6 SP model estimated separately

Independent Variable	Estimated Coefficient	t-statistic
Dummy(I-90)	1.566	1.740
Dummy(US-20)	-0.241	-0.259
Dummy(I-94)	2.510	2.862
Time(I-90)	-8.992e-002	-4.083
Time(US-20)	0.12	3.029
Time(I-94)	-9.418e-002	-4.965
Time(Ridge Rd.)	1.074e-002	0.218
Vfam(Ridge Rd.)	1.331	2.611
Experience(I-94)	1.871e-002	2.529
Chicago(I-90)	3.271	7.297
Chicago(I-94)	1.991	5.028
West(US-20)	-2.096	-4.667

Summary Statistics

No. of observations = 363

$L(0) = -503.22$ $L(\hat{\beta}) = -405.55$

$\rho^2 = 0.194$ $\bar{\rho}^2 = 0.170$

Table 5.7 Combined model estimated using SP and RP data

Independent Variable	Estimated Coefficient	t-statistic
Dummy(I-90)	1.893	0.662
Dummy(US-20)	0.634	0.212
Dummy(I-94)	2.769	0.985
Time(I-90)	-0.553	-8.233
Time(US-20)	-0.388	-3.676
Time(I-94)	-0.496	-7.774
Time(Ridge Rd.)	-0.645	-3.796
Vfam(Ridge Rd.)	5.097	3.349
Chicago(I-90)	5.796	4.901
Chicago(I-94)	4.757	4.238
Male(I-90)	2.226	2.712
Male(I-94)	1.669	2.121
Experience(I-94)	1.155e-002	2.677
West(US-20)	-0.671	-1.934
Scale Factor(μ)	0.1537	6.56

Summary Statistics

No. of observations = 726

$L(0) = -1006.4$ $L(\hat{\beta}) = -652.74$

$\rho^2 = 0.351$ $\bar{\rho}^2 = 0.337$

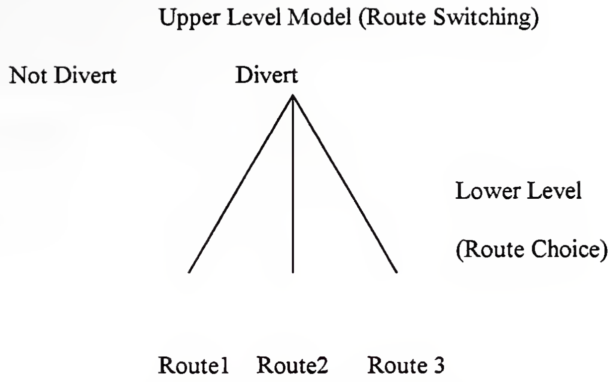

Figure 5.1 Structure of the Nested Logit Model

Table 5.8 Lower Level Model

Independent Variable	Estimated Coefficient	t-statistic
Dummy(I-90)	1.469	2.939
Dummy(US-20)	1.918	6.042
Dummy(I-80)	2.817	5.061
female(I-80)	0.966	1.813
old(I-80)	0.871	2.246
Vfam(I-90)	-1.461	-2.389
Vfam(US-20)	-1.548	-2.597
Chicago(I-90)	1.497	3.085
west(I-90)	-1.946	-2.959
west(US-20)	-1.999	-4.067

Summary Statistics

No. of observations = 260

L(0) = -285.64 L ($\hat{\beta}$) = -212.47

ρ^2= 0.256 $\bar{\rho}^2$= 0.221

Table 5.9 Upper Level Model

Independent Variable	Estimated Coefficient	t-statistic
One	1.343	1.867
old	-0.880	-2.442
purpose_work	0.951	2.277
duration	0.428	6.656
aopp	-9.688e-002	-4.825
copp	-2.775e-002	-2.651
distance	-0.161	-3.099
$\hat{I}^{*}_{divert}$	0.126	0.627
time	0.652	8.189

Summary Statistics

No. of observations = 363

L (0) = -251.61 L($\hat{\beta}$) = -102.43 ρ^2=0.593 $\bar{\rho}^2$=0.557

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

Traditional survey methods to collect data on stated and revealed preferences of motorists have typically resorted to the use of mailback questionnaires, the use of which may result in biased data. In recent years, simulators which provide an artificial environment for the hypothetical scenario have evolved to be an indispensable tool for collecting stated preference data. However, contemporary research adopting such simulators has restricted itself to surveying subjects who are either university students and/or people who are paid to participate in such surveys. These data are obviously not representative of the actual motorists on the road and hence any models developed or forecasts made using such data are questionable. This report presents a novel method of conducting surveys to capture the responses of motorists to hypothetical situations. The survey constitutes the use of a driving simulator and the respondents are actual motorists in the study network, who use the rest areas. Hence the respondents to the survey are in the perfect frame of mind and situation to respond to questions relating to their travel choices. The simulator used in such studies of choice behavior need not have to the state of the art in terms of simulating the driving conditions since the purpose of this survey is not to test and evaluate the driving ability of drivers, but rather to record the choices made by drivers under different situations that they might encounter in real life.

The various choices made by the motorists were modeled using switching models, multinomial choice models, and nested models. The models developed in this report highlight the significance, in the choice process, of the various attributes associated with incidents such as their duration, and location relative to the motorists and their destination. Factors relating to the location of the incident have usually been neglected in previous studies of choice behavior under incident situations.

One of the key conclusions of this report is that the decision to divert from the usual route under incident situations constitutes a multidimensional choice. In other words, the decision to divert consists of two underlying decisions, namely the decision to switch from the current route and the choice of the route to switch to. Hence the choice set of every individual, faced with an incident on his/her usual route, consists of a subset of choices that are correlated. The nested logit model structure was shown to appropriately represent such a choice situation. The validity of this nested structure demonstrated in this report highlights the deficiencies in using a simple switching model or a multinomial choice model for such scenarios.

6.2 Future Work

In this report several models relating to the choice behavior of motorists were developed and a new methodology was proposed to model route diversion in the presence of incidents/congestion. However, these models were developed based on certain simplifying assumptions and future work in this area could eliminate these assumptions and make such models more applicable to real world situations. Some directions for future work are outlined below.

- The models developed in this report were based on the assumption that the motorist receives information from a single source such as an In-vehicle Navigation System.

However, in the real world, the motorists will have the liberty to choose from a variety to sources such as IVNS, HAR, CMS, and other agencies providing advanced traffic information. Hence the choice of a particular information source introduces another dimension into our problem of modeling the choice behavior. Here again the nested model structure appears to provide a feasible solution, but further research and data collection efforts are required to validate this.

One of the sources of information influencing a driver's decision is his/her own perception and knowledge about the network, which gets updated every time he/she drives through the network. This aspect of the driver's perception was not accounted for in the models developed and the development of such models requires significant data collection.

LIST OF REFERENCES

Abdel-Aty, M. A., Kitamura, R. and Jovanis, P. P. (1995), "Investigating the Effect of Travel Time Variability on Route Choice Using Repeated-Measurement Stated Preference Data ", Transportation Research Record 1493, pp. 39-45. TRB, National Research Council, Washington, D. C.

Abdel-Aty, M. A., Vaughn, K. M., Kitamura, R., Jovanis, P. P. and Mannering, F. L. (1994), "Models of Commuters' Information Use and Route Choice: Initial Results Based on a Southern California Commuter Route Choice Survey", Transportation Research Record 1453, pp. 46-55. TRB, National Research Council, Washington, D. C.

Antonisse, R. W., Daly, A. J. and Ben-Akiva, M. (1989), "Highway Assignment Method Based on Behavioral Models of Car Drivers' Route Choice", Transportation Research Record 1220 , TRB, National Research Council, Washington, D. C

Arnott, R., de Palma, A. and Lindsey, R. (1991), "Does Providing Information to Drivers Reduce Congestion?", Transportation Research - A 25A(5), pp. 309-318.

Bates, J. (1988), "Econometric Analysis in Stated Preference Analysis", Journal of Transport Economics and Policy 22(1), pp. 59-69.

Ben-akiva, M., de Palma, A. and Kaysi, I. (1991), "Dynamic Network Models and Information Systems", Transportation Research-A 25A(5), pp. 251-266.

Ben-Akiva, M and Lerman, S. (1985), "*Discrete Choice Analysis*", The MIT press, Cambridge, MA

Ben-Akiva, M. and Morikawa, T. (1990), "Estimation of Switching Models from Revealed Preferences and Stated Intentions", Transportation Research-A 24-A(6), pp. 485-495.

Bonsall, P and Parry, T (1991), "Using an Interactive Route-Choice Simulator to Investigate Drivers' Compliance with Route Guidance Advice", Transportation Research Record 1306, pp. 59-68. TRB, National Research Council, Washington, D. C.

Bovy, P. H. L and Stern, E. (1990), "*Route Choice: Way Finding in Transportation Networks*", Kluwers Academic Publishers, Boston.

Caplice, C. and Mahmassani, H. S. (1992), "Aspects of Commuting Behavior: Preferred Arrival Time, Use of Information and Switching Propensity", Transportation Research-A 26A(5), pp.409-418.

Chen, P. S. and Mahmassani, H. (1993), "A Dynamic Interactive Simulator for the Study of Commuter Behavior Under real Time Traffic Information Supply Strategies", Presented at the 72nd Annual Meeting of the Transportation Research Board, Washington, D.C.

Dougherty, M and Joint, M. (1992), "A behavioral Model of Driver Route Choice using Neural Networks", in Ritchie, S. G. and Hendrickson, C, eds, "Artificial Intelligence Applications in Transportation Engineering", pp. 91-110.

Dubin, J. A. and Rivers, R. D. (1988), *SST User's Guide and Reference Manual.*

Fowkes, T and Wardman, M. (1988), "The Design of Stated Preference Travel Choice Experiments", Journal of Transport Economics and Policy 22(1), pp. 27-44.

Hensher, D. A., Barnard, P. O. and Truong, T. P. (1988), "The Role of Stated Preference Methods in Studies of Travel Choice", Journal of Transport Economics and Policy 22(1), pp. 45-58.

Iida, Y., Akiyama, T. and Uchida, T. (1992), "Experimental Analysis of Dynamic Route Choice Behavior", Transportation Research - B 26B(1), pp. 17-32.

Jou, R. and Mahmassani, H. S. (1994), "Comparability and Transferability of Commuter Behavior Characteristics Between Cities: Departure Time and Switching Decision", Presented at the 73rd Annual Meeting of the Transportation Research Board, Washington, D.C.

Khattak, A. J., Goulias, K. G. and Khattak, A. J. (1996), "A Comparison of Traveler Perceptions Regarding Traffic Congestion and Route Selection Behavior Across Chicago, San Francisco, and Centre County", Presented at the 75th Annual Meeting of the Transportation Research Board, Washington, D.C.

Khattak, A., Kanafani, A. and Le Colletter, E. (1994), "Stated and Reported Route Diversion Behavior: Implications on the Benefits of A.T.I.S", Transportation Research Record 1464, pp. 28-35. TRB, National Research Council, Washington, D. C.

Khattak, A., Polydoropoulou, A. and Ben-Akiva, M. (1995), "Commuters Normal and Shift Decisions in Unexpected Congestion: Pre-Trip Response to A.T.I.S", Presented at the 74th Annual Meeting of the Transportation Research Board, Washington, D.C.

Mannering, F. L. (1989), "Poisson Analysis of Commuter Flexibility in Changing Routes and Departure Times", Transportation Research-B 23-B(1), pp. 53-60.

Khattak, A. J., Schofer, J. L. and Koppelman, F. S. 1991, "Factors Influencing Commuters' En Route Diversion Behavior in Response to Delay", Transportation Research Record 1381.

King, G. F. and Mast, T. M. (1987), "Excess Travel: Causes, Extent, and Consequences", Transportation Research Record 1111, pp. 126-133. TRB, National Research Council, Washington, D. C.

Koutsopoulous, H. N. and Lotan, T. (1990), "Motorist Information Systems and Traffic Congestion: Sensitivity Analysis of Expected Results.", Transportation Research Record 1281.

Koutsopoulous, H. N., Lotan, T. and Yang, Q. (1994), "A Driving Simulator and its Application for Modeling Route Choice in the Presence of Information", Transportation Research-C 2-C(2), pp. 91-107.

Koutsopoulous, H., Polydoropoulou, A. and Ben-Akiva, M. (1993), "Public Acceptance and User Response to A.T.I.S Products and Services: The Use of travel Simulators to Investigate the response to traffic Information", Technical Report, Volpe National Transportation Systems Center, Cambridge, MA.

Kroes, E. P. and Sheldon, R. J. (1988), "Stated Preference Methods", Journal of Transport Economics and Policy 22(1), pp. 11-25.

Lotan, T. and Koutsopoulous, H. N. (1993), "Route Choice in the Presence of Information Using Concepts From Fuzzy Control and Approximate Reasoning", Transportation Planning and Technology 17, pp. 113-126.

Madanat, S. M., Yang, C. Y. D. and Yen, Y. M. (1995), "Analysis of Stated Route Diversion Intentions Under A.T.I.S Using Latent Variable Modeling", Transportation Research Record 1485, pp. 10-17. TRB, National Research Council, Washington, D. C.

Mannering, F. L., Kim, S. G., Barfield, W., and Ng, L. (1994), "Statistical Analysis of Commuters' Route, Mode, and Departure Time Flexibility and the Influence of Traffic Information", Presented at the 73rd Annual Meeting of the Transportation Research Board, Washington, D. C.

Noland, R. B. and Small, K. A. (1995), "Travel Time Uncertainty, Departure Time Choice, and the Cost of the Morning Commute", Presented at the 74th Annual Meeting of the Transportation Research Board, Washington, D.C.

Polydoropoulou, A., Ben-Akiva, M. and Kaysi, I. (1995), "Influence of Traffic Information on Drivers' Route Choice Behavior", Transportation Research Record 1453, pp. 56-65. TRB, National Research Council, Washington, D. C.

Schofer, J. L., Khattak, A. and Koppelman, F. S. (1993), "Behavioral Issues in the Design and Evaluation of Advanced Traveler Information Systems", Presented at the 72nd Annual Meeting of the Transportation Research Board, Washington, D. C.

Vaughn, K. M., Abdel-Aty, M. A., Kitamura, R., Jovanis, P. P., Yang, H., Kroll, N. E. A., Post, R. B. and Oppy, B. (1993), "Experimental Analysis and Modeling of Sequential Route Choice Under A.T.I.S in a Simplistic Traffic Network", Transportation Research Record 1408, TRB, National Research Council, Washington, D. C.

Vaughn, K. M., Reddy, P., Abdel-Aty, M. A., Kitamura, R. and Jovanis, P. P. (1995), "Route Choice and Information Use: Initial Results From Simulation Experiments", Presented at the 74th Annual Meeting of the Transportation Research Board, Washington, D.C.

Wardman, M. (1988), "A Comparison of Revealed Preference and Stated Preference Models of Travel Behavior", Journal of Transport Economics and Policy 22(1), pp. 71-84.

Wardman, M. (1991), "Stated preference Methods and Travel Demand Forecasting: An Examination of the Scale Problem", Transportation Research-A 25A(2/3), pp.79-89.

Wenger, M. J., Spyridakis, J. H., Haselkorn, M. P., Barfield, W. and Conquest, L. (1990), "Motorist Behavior and the Design of Motorist Information Systems", Transportation Research Record 1281. TRB, National Research Council, Washington, D. C.

Yang, H., Kitamura, R., Jovanis, P. P., Vaughn, K. M. and Abdel-Aty, M. A. (1993), "Exploration of Route Choice Behavior with Advanced Traveler Information using Neural Network Concepts", Transportation 20(2), pp. 199-223.

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