Final Report

DESIGN AND DEVELOPMENT OF A COMPUTER SIMULATION EXPERIMENT TO SUPPORT MODE/ROUTE CHOICE MODELING IN THE PRESENCE OF ATIS

Dr. Mohamed Abdel-Aty, PE

Civil and Environmental Engineering Department
University of Central Florida
Orlando, Florida

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EXECUTIVE SUMMARY

The implementation of Advanced Traveler Information Systems (ATIS) technologies into transportation systems is limited and is still in the early stages of development. As data collecting tools for route choice modeling purposes under ATIS, researches have used mailed-in surveys, telephone surveys and Internet surveys. However, in the recent years, they have used computer simulation programs as data collection tools to have a better understanding of drivers' behavior under ATIS. This study presents the design and development of an interactive computer simulation tool. This simulation tool is being used to run subjects through several travel scenarios, in which each subject is required to make mode and route choices in the existence of ATIS. A portion of the Orlando network has been captured from a GIS database. Both driver and transit information are included. Types and levels of information are addressed. A visual basic program has been developed to capture this roadway network and simulate a moving vehicle on the network.

A subject has the ability to move the vehicle on different segments of the network using the computer's mouse. Different levels of information are provided to the subjects, including transit and route information, pre-trip and en-route information, and information with and without advice. The subject makes different travel choices while he/she travels on the network from a specified origin to a specified destination. Different travel congestion levels are also provided. All the travel decisions are captured and coded to a database for analyses. The experiment starts and ends with a short survey to collect the subjects' socio-demographic characteristics, and preferences and perceptions. This simulation is unique since it combines route and mode choices under ATIS in a real network environment.

The objectives of this effort are to develop a simulation tool that would enable us to incorporate mode and route choices with ATIS effect in one effort, achieve better understanding of the complex travelers' decisions, and investigate the multi-modal aspect of travel, and collect data that support the incorporation of the effect of ATIS in travel models. The research also aims to answer the following question; what will be the travelers' choices (mode and route choices) if the technology allows them to have real-time pre-trip and en-route traffic information on the network.

While the main objectives of the research were the design and development of the simulation, a preliminary pilot study was conducted by running 10 subjects through the simulation. The subjects were recruited from the University of Central Florida (UCF) where they work/study. It has been shown that the subjects ran the simulation smoothly, friendly, and without confusion. The simulation database file is checked and found to have the correct coded information. ANOVA and descriptive statistics have been applied to the data of this pilot study. Two modeling efforts are introduced. The first modeling presents a nested logit model. A nested logit model is used to analyze and understand the complex travelers' decisions in the mode/route choices. The second modeling effort is based on applying binomial logit/probit models to predict en-route short-term choice (link choice). The travel time is found to be significant in all models. The modeling results also showed that, as the frequency of receiving en-route traffic information increases the probability of a driver to choose the expressway system decreases. The results showed that 33.33% of the drivers followed the advised route without any diversion until the destination, when they were provided with pre-trip information. While, 8.33% followed the updated en-route advised route link-by-link from the current position to the destination.

While this was a small project with limited funding level, the main contribution of this research is the design and development of the simulation program. Future research is still needed to collect more data and to develop different route/mode choice models that account for the different types/levels of information that the simulation can produce.

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CHAPTER 1

INTRODUCTION

1.1 Background

The implementation of ATIS technologies into real transportation systems is limited and is still in the early stages of development. Due to the lack of real-world environments in which driver behavior, under the influence of ATIS, can be observed, experimental methods of analysis must be developed. Also, based on the literature, it is found that, modeling pre-trip and en-route travel decisions of commuters and examining factors that influence route switching in response to real time traffic information still need more research. More research to elaborate and have a better understanding of the travelers' complex decisions. However, most of the previous studies were based on data collected through mail-back surveys, Internet surveys, and field studies. Few studies have used computer simulation as a data collection tool. Most of these studies used a theoretical network. Moreover, the previous studies did not include the transit option (bus) and drive option using a simulated car in one effort. Therefore, in this study a unique realistic simulation tool for route and mode choice data collection is developed.

1.2 Research Objectives

The objectives of this effort are to develop a simulation tool that would enable us to incorporate mode and route choices with ATIS effect in one effort, achieve better understanding of the complex travelers' decisions, and investigate the multi-modal aspect of travel, and collect data that support the incorporation of the effect of ATIS in travel models. The research also aims to answer the following question; what will be the travelers' choices (mode and route choices) if the technology allows them to have real-time pre-trip and en-route traffic information on the network.

1.3 Organization of the Report

Following this introductory chapter, a detailed literature review of the recent studies adopted in order to understand the drivers' choices, and in particular their choices when influenced by ATIS are presented in Chapter 2. This literature chapter is divided into 4 parts: first, the data collection tools, second, the results of the previous mode choice studies, third, the results of the previous route choice studies, and finally, the previous statistical techniques applied in mode and route choice modeling. Chapter 3 describes the statistical models used in this study. Four main approaches presented in this chapter: binomial logit/probit models, multinomial logit models, multinomial probit models, and nested logit models. Chapter 4 presents the components of the simulation from both a designer point of view and user point of view. Each scenario of the different 5 scenarios of the simulation has been introduced in detail. Chapter 5 describes the output database file of this simulation with its four tables. Chapter 6 presents a pilot's study results and preliminary initial modeling effort. Finally, Chapter 7 presents conclusions of the study.

CHAPTER 2

LITERATURE REVIEW

2.1 Background

This chapter reviews the recent studies conducted to understand the drivers' choices, and in particular their choices when influenced by an Advanced Traveler Information System (ATIS). Different approaches were used in these studies: field experiments, route choice surveys, interactive computer simulation games, and route choice simulation and/or modeling. These studies are classified according to the main approach used, and the main objective, method, modeling, and findings are presented. Due to the lack of real-world environment in which driver behavior, under the influence of ATIS, can be observed, experimental methods of analysis must be developed. The crux of the problem is that ATIS technologies will not proliferate until a better understanding of the possible impacts of ATIS on the transportation system is reached. Yet, without ATIS technologies in place it is very difficult for researchers to study the effects of ATIS on driver behavior and define these possible impacts. This literature summarizes these techniques and describes how they have been utilized in the literature and significant findings are discussed.

2.2 Data Collection Methods

2.2.1 Route Choice Surveys/Interviews

The survey approach enables the researcher to analyze the effects of ATIS directly from the reported behavior and perceptions of the individual system users. A large-scale survey can achieve a sample size that adequately supports quantitative modeling and forecasting. A better representation of the population in a survey can also facilitate better understanding of actual human behavior and decision processes.

Khattak et al. (1993) examined short-term commuter response to unexpected (incident-induced) congestion using a data collected through a survey of travelers. About 2000 drivers from randomly selected parking garage were given mail-back survey. Abdel-Aty et al. (1995) investigated commuters' route choice behavior in the presence of traffic information. Data used in the study were collected from two waves of computer aided telephone interviews targeting the morning commuters in the Los Angeles area. Harris et al. (1995) conducted another telephone survey as part of developing a strategy for implementing an Intelligent Transportation System (ITS) in the 16-county, New York metropolitan area.

Hatcher et al. (1992) observed route and trip scheduling decisions for evening commuters using a two-stage survey. Asakura et al. (2000) gathered data through an Internet survey to address the process in which drivers make use of traffic information. Mahmassani et al. (2000) examined behavioral responses of non-commuters under real-time information during shopping trips using an Internet survey. Jou (2001) investigated the impact of pre-trip information on automobile commuters' choice behavior. Analysis was based on an extensive home-interview survey of commuters in a metropolitan area in Taiwan. In a recent study by Kim et al. (2002), a survey designed and used to investigate drivers' responses to traffic information has been conducted in the Daegu metropolitan city. Abdel-Aty (2001) conducted a computer-aided telephone interview in two metropolitan in northern California. The survey included an innovative stated preference design to collect data that address the potential of advanced transit information systems

2.2.2 Field Studies and Experiments

Field Experiments are the most accurate and representative method to understand the effects of ATIS on drivers' behavior. ATIS experiments facilitate the observation of drivers in the real traffic environment. Data recorded in this manner are an accurate representation of driver behavior because these are real decisions being made in a real traffic environment. However, gaining this accurate representation involves a high cost. In addition, experiments in the transportation field tend to require cooperation and coordination among various agencies, and can be difficult to monitor. The results of an experiment are known either by observing the overall performance, or by interviewing the drivers involved.

Bonsall (1991) presented results of a survey of drivers equipped with a route guidance system as part of the Berlin LISB (Leit and Information System Berlin) trial. Self-completion questionnaires were administered among a subset of about l00 drivers of LISB-equipped cars at three stages; before any guidance was provided, during the static guidance phase, and again during the dynamic guidance phase (one-group pretest post test design).

Jitendra et al. (2000) used a state-of-the-art image processing and tracking algorithms system in an attempt to attain higher levels of accuracy and reliability than have yet been achieved in ATIS in real time. This system detects vehicles on the road, tracks their progress through the camera's field of view, identifies each vehicle by generic type (car, van, truck, etc.), and returns coarse information such as traffic speed and flow.

2.2.3 Interactive Computer Simulation Games

In the recent years, researchers have used computer simulation programs as data collection tools to study the travelers' behaviors under ATIS. Vaughn et al. (1993) performed an experiment to collect sequential route choice data under the influence of ATIS using a personal computer-based simulation. The network was a simple hypothetical network consisted of a freeway and a side road where each of them was a single link going from the fixed origin to the fixed destination. The simulation begins by presenting a set of instructions to the subjects describing how the program operates. At each trial day, the subjects were given an advice that might or might not be correct. Subjects were instructed that their main task was to minimize their overall travel time by deciding when and when not to follow the advice provided by the traffic information system. The experiment collected information on drivers' pr-trip route choice behavior at three levels of information accuracy: 60, 75, and 90 percent.

Vaughn et al. (1995) designed and conducted a computer based simulation experiments utilizing 100 regular commuters from the Sacramento California region. Computer based simulation was used to create a hypothetical traffic network and as a tool for collecting dynamic route choice data. The hypothetical network was composed of three primary routes from a fixed origin to a fixed destination. The primary routes were composed of a freeway route and two arterial routes. These primary routes were cross connected with a series of surface streets creating a network of 34 roadway links and 23 intersections (or potential decision points). While this network was simplistic in comparison to the real traffic environment it was a considerable step up in complexity from the two-link, two-node traffic network utilized in the first set of experiments.

Adler et al. (1993) developed an interactive microcomputer-based animated simulator to model en-route driver travel choices in the presence of advanced traveler information systems. The advantages of this simulator were realized in its versatility to model driver decision processing while presenting a realistic representation of the travel choice domain.

Yang (1994) created a computer experiment where each subject was required to run 32 simulated days. At each run, a subject was guided to choose between the freeway or a side road. The results indicated that most subjects made route choices based mainly on their recent experiences. It was also demonstrated that route choice behaviors are related to the personal characteristics as well as the characteristics of the respective routes.

Kitamura et al. (1995) conducted in-laboratory interviews with approximately 50 subjects who used a personal computer (PC)-based information system prototype during the interview sessions. The menu-driven prototype conveyed information on the bus transit system in Davis, California. The subjects were recruited from the nearby Sacramento metropolitan area while controlling for age and sex. The objectives of the study were: 1) to determine which types of information are more important to the user; 2) to examine whether an exposure to the information system alters the users' perception of transit attributes and their attitudes toward public transit; and 3) to assess user receptiveness of such an information system.

Mahmassani et al. (1999) addressed departure time and route switching decisions made by commuters in response to ATIS. It was based on the data collected from an experiment using a dynamic interactive travel simulator for laboratory studies of user responses under real-time information. The experiment involved actual commuters who simultaneously interacted with each other within a simulated traffic corridor that consisted of alternative travel facilities with differing characteristics. These commuters could determine their departure time and route at the origin and their path en-route at various decision nodes along their trip.

Chen et al. (1999) examined the processes underlying commuter decisions on en-route diversions and day-to-day departure time and route choices as influenced by the provisions of real-time traffic information. This study presented a series of large-scale laboratory-like experiments in which real commuters interacted with and among multiple participants in a traffic network in real-time under various information strategies through a dynamic travel simulator.

Lerner et al. (2000) investigated the pre-trip and en-route decision processes that typify driver decision making about route choices and route diversion. The trips included morning home-to-work commutes, evening work-to-home commutes, evening or weekend trips to an unfamiliar shopping mall, and weekday, off-peak trips to a downtown business area. Twenty-four paid participants took part, all in the greater Washington, DC, area. Each participant received extensive training, via a training video and a supervised training session, before being provided with an in-vehicle video recording system and recording specified trips. The information collected included pr-trip information sources and decisions, and continuous en-route commentary on information sources, decisions questions, strategies, major concerns, information needs, and errors. At the conclusion of each trip, additional information was collected on the drivers' perception of various aspects of the trip and the related information sources and needs.

2.3 Results of Previous Mode Choice Studies

Many previous studies have investigated the effect of information on drivers' behavior and route and departure time choices. However, few studies have attempted to explore the potential of information on transit ridership. Advanced pre-trip transit information systems can contribute to the improvement of transit service levels by providing their users with information on transit routes, schedules, fares, and opportunities around transit stops. By providing information and possibly changing the users' attitudes toward public transit, such systems may also entice more travelers to public transit (Kitamura et al., 1995). This section summarizes some of these studies and their findings.

Hansen et al. (1994) identified opportunities to improve transit performance using Advanced Public Transportation System (APTS) Technologies, assessed transit operator viewpoints on and experiences with APTS technologies, and proposed how current adoption and utilization practices might be improved so that these technologies are used in a more efficient and effective manner. The research consisted of three main phases: 1) identification of APTS technologies and development of a framework for assessing their potential value in improving transit system performance; the technologies considered were automatic vehicle monitoring (AVM); advanced traveler information systems (ATIS); and advanced fare payment systems (AFP); 2) identification and study of 7 case studies of individual transit operators chosen to include properties that have adopted APTS technologies as well as those that have not; and 3) design and conduction of a transit operator survey, in which 52 transit operators, 37 of which had adopted at least one APTS technology and 15 had not, were included.

Kitamura et al. (1995) indicated that route maps and schedules are the most important pieces of information when planning a transit trip to a specific destination by a specific time. The study results pointed to the need for automated route searching capabilities, i.e., the user inputs the origin, destination, and the time by which he/she whishes to depart from the origin or arrive to the destination, then the system offers recommended bus lines.

Harris et al. (1995) concluded that nearly all peak-hour travelers in the metropolitan area desire enhanced, real-time travel information systems and are willing to pay at least something for access to such information. The most valued information was identification of the locations and extent of delays, travel times of alternate routes, and arrival times of transit vehicles. Based on past responses to information on delays, the most common responses would be to alter departure times, followed by changing routes; changes of mode would occur only with forecasts of significant delay. Nearly all means of obtaining the information were highly favored, but the most popular among motorists, a dedicated traffic information radio station and informative variable message signs, were readily available.

Abdel-Aty (2001) illustrated that the commuters seek several types of transit information, including information about: operating hours, frequency of service, fare, transfers, seat availability, and waking time to transit stop. In general the results indicated the potential of transit information for certain groups of the population. About 38% of non-transit users indicated that they might consider transit use if appropriate transit information was available to them. About half of them indicated that they were likely to use transit if their preferred information types were provided. However, this survey did not investigate a system that would provide integrated information for both transit and traffic, and estimates travel times by both transit and driving together with delay estimates. It would not be unrealistic in cases of substantial delays that more drivers would use transit. This survey results indicate a promising effect of transit information on transit ridership, however more investigation need to be done to reach accurate estimates of mode changing that would result from accurate and updated integrated information systems.

2.4 Results of Previous Route Choice Studies

This section summarizes the findings of different studies conducted to study the effect of ATIS on the drivers' route choice behavior. Khattak et al. (1993) concluded that commuters' diversion and return behavior varied with their personal characteristics and the characteristics of the trip they were making at the time when the choice arose. Commuters who made longer trips were significantly more likely to return after diversion. Individuals who used radio traffic information, and those with higher stated preferences for diversion were more likely, but not significantly so, to return to their original route. Individuals oriented to "adventure and discovery" were slightly less likely than others to return to their original route.

Hatcher et al. (1992) found that about 39.3% of evening commuters had one or more stops, where personal business and shopping were the most frequent cause. For each commuter, a stop ratio was calculated by dividing the number of trips with stops by the total number of trips reported. Commuters with high stops ratio (e.g. > 0.7) were likely to make the same stop on many trips. Furthermore, trip chaining significantly influenced route and joint (both route and time switch) switching behavior: trips with stops were much more likely to involve switching than trips without stops. The analysis utilized both a "day-to-day" and a "deviation from normal" approach to switching behavior. In general, commuters tended to change departure times more frequently than routes, possibly a reflection of a limited route choice set in comparison with a broader set of available departure times. Also it was found that travelers with short trips may see no need for altering routes (small absolute time savings), while those with long trips may face too much uncertainty with regard to travel time variability to distinguish one route's superiority over another.

Vaughn et al. (1995) indicated that drivers could rapidly identify the accuracy level of information and that they adjust their behavior accordingly. Evidence also indicated that an accuracy threshold level exists below which drivers will not follow advice and above which drivers readily follow advice. It was also found that male subjects agreed with advice more often than females, that less experienced drivers agreed more often than experienced drivers, and that “freeway bias” exists with drivers much more willing to follow advice to take a freeway route. The model of route choice behavior had a prediction rate that was 79 percent accurate, which also indicated that previous experiences had little effect on current route choices. Mahmassani et al. (2000) indicated that gender, age (greater than 40), level of education (with college degree) and high income (greater than $50,000) are not statistically significant in the explaining either route or destination switching.

In a recent study by Kim et al. (2002), a variable not considered in previous studies, number of stops before arriving work, was significant. It was found also that drivers who are familiar with alternative routes have a high propensity to change their pre-selected routes. It is also shown that traffic information should be provided with alternative route information as well.

2.5 Previous Statistical Modeling Techniques in Route/Mode Choice Modeling

Stochastic modeling of network assignment, or route choice behavior, has historically employed either the multinomial logit (MNL) model or the multinomial probit (MNP) model (Sheffi 1985). The problem with the MNL model is that it does not accurately represent choices among overlapping alternatives, which are bound to comprise any realistic urban transportation network. The problem with the MNP model is that it is so computationally burdensome that it makes infeasible the estimation of choice sets consisting of more than a handful of alternatives. A detailed urban network could present numerous alternatives for any given choice situation.

Abdel-Aty et al. (1994) developed a binary logit model to estimate respondents' choice to accept or reject an ATIS advice. It was showed clearly that ATIS has a great potential in influencing commuters' route choice even when advising a route different from the usual one. Also several socioeconomic factors such as age and gender were found to affect route choice.

Cascetta et al. (1996) specified a route choice model featuring a modification of the MNL model called the C-logit, which penalizes the utility function in the standard MNL by a "commonality factor." The commonality factor is subtracted from the main utility function and represents the overlapping link lengths between a particular route choice and other route choices. The commonality factor reduces the probability of choosing paths that overlap and increases the probability of choosing an independent path. Cascetta offered a few variations of the C-logit in which the commonality factor took on different structural forms. Versions of the C-Logit presented to date represent similarities between routes based on overlapping link lengths, but could be extended to account for other similarities on non-overlapping links.

Abdel-Aty et al. (1997) presented a statistical analysis of commuters' route choice including the effect of traffic information. Two route choice models were estimated. The first model used five hypothetical binary choice sets collected in a computer-aided telephone interview. The objective of the model was to determine how travel time variation affects route choice, and the potential interplay among travel time variation, traffic information acquisition and route choice. The second model used data collected in a mail survey from three binary route choice stated preference scenarios customized according to each respondent's actual commute route and travel time. The objective of the model was to investigate the potential effect of advanced traveler information systems on route choice. The correlation among error components in repeated measurement data was addressed in this paper with individual-specific random error components in a binary logit model with normal mixing distribution.

Yai et al. (1997) introduced a multinomial probit model for route choice behavior in which the covariance matrix was parameterized by a function that represents the overlapped relation between pairs of alternatives. The model was estimated using numerical integration from passenger survey data of the Tokyo metropolitan railway network for choice situations with three alternatives. The authors simplified their model considerably by assuming that the total variances were identical for each alternative and for each individual. They were able to represent the differences between alternatives as a function of distance on overlapping network links and common transfer stations.

Abdel-Aty (1998) provided a methodological approach for modeling drivers' routing decisions in case they encounter incident related problems. The approach presented in this research was to estimate the likelihood of remaining on the same route in case of unusual congestion, whether without any diversion or diverting only around the location of the incident, conditioned on the non-diversion option. It was concluded that a nested logit model which accounted for shared unobserved effects between not diverting and diverting only around the problem provided the best structural fit for the observed distribution of the routing decision in case of an incident. The paper proved the superiority of the nested logit structure over the simple multinomial logit. The variables that entered in the estimated models illustrated the significance of several socioeconomic, commute and perceptual factors on the incident related routing decisions. A factor which was consistently significant was traffic information acquisition. This proves that ITS and specifically ATIS is likely to have a great impact on distributing traffic efficiently in case of an incident.

Ben-Akiva (1999) tried to explore the complex mechanisms governing users' response to the provision of traffic information. A conceptual behavioral framework for the users' adoption process of new ATIS products was operationalized. Models of willingness to pay were estimated and the effect of traffic information on travelers' response was predicted. Still, much remains to be learned about the diffusion of ATIS products and services and the interrelationship between ATIS attributes and travelers decision-making. From a transportation planning point of view, the eminent question was: How can the models developed and the quantitative results obtained in this research be used to evaluate the impact of ATIS on transportation networks? An ATIS impact evaluation framework that explicitly incorporates information from the models developed can be implemented into simulation tools to quantify the impact of travelers' response to ATIS.

Srinivasan et al. (2000) examined route choice, in the presence of real-time information, as a consequence of two underlying behavioral mechanisms: compliance and inertia. The compliance mechanism reflected the propensity of a user to comply with the information supplied by ATIS. The inertia mechanism represented the tendency of a user to continue on his/her current path. A framework was proposed in this paper to explicitly model these mechanisms. This framework decomposed the route choice into two states by exploiting the user's path choice structure and the information supplied by ATIS. In each state, the mechanisms were incorporated by associating their utilities with those that reflected the specific attributes of the alternative paths. The resulting nested choice structure is implemented using the multinomial probit model. This framework was illustrated using route choice data obtained from dynamic interactive simulation experiments.

Mahmassani et al. (2000) examined behavioral responses of non-commuters under real-time information during shopping trips using a stated preferences survey. Utilizing the results from this survey, a discrete choice model was developed to examine factors that influence en-route switching to alternate destinations and routes. The fundamental difficulty in modeling this problem was due to the structure of the survey where the information provided and user choices are interdependent. That is, the choice set presented to a trip maker at a decision state was predicated on his/her previous decision. Conversely, a trip maker's decision in turn alerts his/her information and choice set. To model this problem, a framework was proposed to account for the hierarchical nature of the observed choices. Explanatory variables include tripmaker attributes and transportation system characteristics.

Based on the above literature, it could be concluded that, modeling pre-trip and en-route travel decisions of commuters and examining factors that influence route switching in response to real time traffic information still need more research. However, most of the previous studies were based on data collected through mail-back surveys, Internet surveys, and field studies. Few researchers have used the computer simulations as a data collection tool. Most of these studies used a theoretical network. Moreover, none of the previous studies included a simulation that has a transit option (bus) and drive option in one effort. This dissertation provides a unique mode and route simulation tool. The network that was used is a real network captured from a GIS database of the Orlando area transportation network.

CHAPTER 3

STATISTICAL MODELING TECHNIQUES

3.1 Background

In the context of transportation demand analysis, Discrete Choice models have played an important role in last 30 years. Choice models are referred to as disaggregate models. It means that the decision-maker is assumed to be an individual.These models consider that the demand is the result of several decisions of each individual in the population under consideration. These decisions usually consist of a choice made among a finite set of alternatives. An example of sequence of choices in the context of transportation demand is: choice of an activity (play-yard), choice of destination (6th street), choice of departure time (early), choice of transportation mode (transit) and choice of itinerary (local streets). For this reason, discrete choice models have been extensively used in this study. Discrete choice models are namely used to provide a detailed representation of the complex aspects of transportation demand, based on strong theoretical justifications.

Discrete choice models are powerful but complex. The art of finding the appropriate model for a particular application requires both a close familiarity with the reality under interest and a strong understanding of the methodological and theoretical background of the model. Because of its disaggregate nature, the model has to include the characteristics, or attributes, of the individual. Many attributes, like age, gender, income, may be considered in the model. However, the analyst has to identify those that are likely to explain the choice of the individual. There is no automatic process to perform this identification. The knowledge of the actual application and the data availability play an important role in this process.

3.2 Modeling Assumptions

In order to develop models capturing how individuals are making choices, Specific assumptions have to be made. The assumptions cosidered in this research are:

1. Decision-maker: these assumptions define who is the decision-maker, and what are his/her characteristics;
2. Alternatives: these assumptions determine what are the possible options of the decision-maker;
3. Attributes: these assumptions identify the attributes of each potential alternative that the decision-maker is taking into account to make his/her decision;

3.2.1 Decision Maker

As mentioned above, choice models are referred to as *disaggregate* models. It means that the decision-maker is assumed to be an *individual*. In general, for most practical applications, this assumption is not restrictive. The concept of "individual" may easily been extended, depending on the particular application. It can be considered that a group of pepole (a household or pepole share one car, for example) is the decision-maker. In doing so, we decide to ignore all internal decisions within the group, and to consider only the decision of the group as a whole. In this research, the subject is cosidered to be the decision maker who takes his/her decisions without any external effects. In this study, at the beginning of the simulation, each subject is asked to answer 22 biography questions which are used to describe the decision-maker characteristics.

3.2.2 Alternatives

Analyzing the choice of an individual requires not only the knowledge of what has been chosen, but also of what has *not* been chosen. Therefore, assumptions must be made about options, or alternatives, that were considered by the individual to perform the choice. The set containing these alternatives, called the *choice set*, must be characterized.

A discrete choice set contains a finite number of alternatives that can be explicitly listed. The corresponding choice models are called discrete choice models. The choice of a transportation mode is a typical application leading to a discrete choice set. In this work, the mode/route choice is considered as discrete choice set.

3.2.3 Attributes

Each alternative in the choice set must be characterized by a set of attributes. Similarly to the characterization of the decision-maker described in Section 3.2.1. In the context of a transportation mode choice, the list of attributes for the mode drive could include the travel time, the out-of-pocket cost and the comfort. The list for bus could include the travel time, the out-of-pocket cost, the comfort and the bus frequency. Note that some attributes may be generic to all alternatives, and some may be specific to an alternative (bus frequency is specific to bus). Also, qualitative attributes, like comfort, may be considered.

An attribute is not necessarily a directly observed quantity. It can be any function of available data. For example, instead of considering travel time as an attribute, the logarithm of the travel time may be considered. The out-of-pocket cost may be replaced by the ratio between the out-of-pocket cost and the income of the subject. The definition of attributes as a function of available data depends on the problem. Several definitions must usually be tested to identify the most appropriate.

3.3 Binomial Logit/Probit Models

Both the binomial logit model and the binomial probit model are an estimation technique for equations with dummy dependant variables that avoids the unboundedness problem of the linear probability model by using a variant of the cumulative logistic function in the logit model and cumulative normal distribution function in the probit model as follows:

First for the binomial logit; $\ln\left(\frac{D_i}{1-D_i}\right)=\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+.......+\varepsilon_i$ where D_i is a dummy variable, the expected value of D_i continues to be Pi, the probability that the i_{th} person will make the choice described by $D_i = 1$. Consequently, the dependent variable of the last equation can be thought of as the log of the odds that the choice in question will be made. Logits cannot be estimated using ordinary lease square method (OLS). Instead, the maximum likelihood is used, an iterative estimation technique that is epically useful for equation that are nonlinear in the coefficients.

Second for the binomial probit; $$P_i=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{Z_i} e^{-s^2/2}ds$$

where: P_i = the portability that the dummy variable $D_i = 1$

Zi = $\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}$

S = a standardized normal variable

The probit estimation procedure uses more computer time than does the logit but the probit estimation is quite theoretically appealing because many statistics variables are normally distributed.

Both binomial logit model and binomial probit model are used in this research to test the effect of the drivers' characteristics as well as the effect of the travel time of the chosen and not-chosen link on their short-term choices or what is called "link choice". Both models will be used also in this report as a system of (n-1) binomial equations for the route choice between *n* routes.

3.4 Multinomial Logit Models

Multinomial logit models have been used extensively in transportation planning to understand: how people select their mode of travel (driver, car pooling, transit), when people prefer doing their trips, and many other aspects. In case of travel mode choice, the hypothesis underlying multinomial logit models is that when an individual faced with a choice situation, his/her preferences towards each alternative can be described by an attractiveness measure associated with each alternative. This attractiveness can be described as function of attributes of the alternatives as well as the decision-maker characteristics.

The decision maker is assumed to choose the alternative that yields the highest attractiveness. Let $A = (A_1,\ldots,A_k)$ denote the vector of attractiveness associated with a given set of alternative, κ. This set includes K alternatives numbered 1, 2, …,K. Let **a** denote the vector of variables which include these characteristics and attributes. To incorporate the effects of unobserved attributes and characteristics, the attractiveness of each alternative is expressed as a random variable consisting of deterministic component, $V_K(a)$ and an additive random "error term", $\zeta_i(\theta,a)$, that is,

$$A_i(\theta,a) = V_i(\theta,a) + \zeta_i(\theta,a) \qquad \forall\, i \in \kappa$$

The measured attractiveness functions $V_i(\theta,a)$ may take any finite real values and they need not be related in any way. The random disturbances $\zeta_i(\theta,a)$ can be interpreted as capturing different things, among them, errors in the measurement of the attributes in the data and the contribution of neglected attributes (attributes that can not be observed). If a joint distribution of the error terms $\zeta_i(\theta,a)$,or that of $A_i(\theta,a)$, is known and attractiveness functions are specified, it is possible to obtain the choice function by calculating the probability that alternative i is the most attractive:

$$P_i(\theta,a) = \Pr\,\{V_i(\theta,a) + \zeta_i(\theta,a) > V_j(\theta,a) + \zeta_j(\theta,a);\ \forall j \neq i\} \qquad i,j \in \kappa$$

$$P_i(\theta,a) = \Pr\,\{V_i(\theta,a) - V_j(\theta,a) > \zeta_j(\theta,a) - \zeta_i(\theta,a);\ \forall j \neq i\} \qquad i,j \in \kappa$$

McFadden (1974) assumed that error terms ζ are independent identically distributed Gumbel variates (i.e., $F(\zeta) = \exp(-\exp(\zeta))$). Then the above equation can be reduced to the multinomial logit model (MNL) as follow :

$$P_n(i) = \frac{e^{\beta_i X_n}}{\sum_{i=1}^{K} e^{\beta_i X_n}} \qquad ;\ i = 1, 2, \ldots, K$$

where $P_n(i)$ is the probability that person n will choose alternative i, X_n is a vector of measurable characteristics, and β_i is a vector of estimable coefficients by standard maximum likelihood methods. Then the asymptotic t-test is used to test whether a particular parameter in the model differs from zero. The likelihood ratio test is used to test the overall goodness of fit.

One of the most widely discussed aspects of the multinomial logit model is the independence from irrelevant alternatives property, or IIA. The IIA property holds that for a specific driver the ratio of the choice probabilities of any two severity levels is entirely unaffected by any other alternatives. The IIA can be easily shown to hold in the case of multinomial logit models as follows:

$$P_n(i) / P_n(j) = \left(\frac{e^{\beta_i X_n}}{\sum_{I} e^{\beta_i X_n}}\right) / \left(\frac{e^{\beta_j X_n}}{\sum_{I} e^{\beta_i X_n}}\right) = \frac{e^{\beta_i X_n}}{e^{\beta_j X_n}} = e^{(\beta_i - \beta_j) X_n}$$

McFadden (1977) investigated a wide range of computationally feasible tests to detect violations of the IIA assumption. This involves comparisons of logit models estimated with subsets of alternatives from the universal choice set. If the IIA assumption holds for the full choice set, then the logit model also applies to a choice from any subset of alternatives. Thus, if the logit model is correctly specified, we can obtain consistent coefficient estimates of the same sub-vector of parameters from a logit model estimated with the full choice set and from a logit model estimated with a restricted choice set.

The multinomial logit models are used in this study as route choice models. I also intend to extend their use to predict the difference between the travel time of the chosen route and the minimum travel time on the network for the same trial.

3.5 Multinomial Probit Models

The problem with the MNL model is that it does not accurately represent choices among overlapping alternatives, which are bound to comprise any realistic urban transportation network.

The MNL model assumes the error terms are identically and independently distributed (IID). The independence assumption leads the IIA. In the case of route choice, this property can best be illustrated by a simple network with three possible paths between one origin and one destination. All three paths have the same generalized cost or travel time, but two of the paths overlap for a large portion of their respective lengths. The MNL would find that all three paths had an equal probability of being chosen, when common sense suggests that the two overlapping paths should be treated like one alternative with minor variations.

The IID assumption on the random components can be relaxed in the Multinomial probit model (MNP). In this model, the individual's choice among J alternatives is the one with maximum utility, where the utility function is

$$U_{ij} = \beta' x_{ij} + \varepsilon_{ij}$$

where

U_{ij} = utility of alternative j to individual i

x_{ij} = union of all attributes that appear in all utility functions. For some alternatives, $x_{ij}(k)$ may be zero by construction for some attribute k which does not enter the utility function for alternative j.

ε_{ij} = unobserved heterogeneity for individual i and alternative j.

The multinomial logit model specifies that ε_{ij} are drawn from independent extreme value distributions (which induces the IIA condition). In the multinomial probit model, we assume that ε_{ij} are normally distributed with standard deviations $SDV[\varepsilon_{ij}] = \sigma_j$ and unrestricted correlations $COR[\varepsilon(i,j), \varepsilon(j,l)] = \rho(j,l)$ (the same for all individuals). Observations are independent, so Cor[ε (i,j), ε(t,l)] = 0 if i is not equal to t, for all j and l. The number of alternatives must be fixed - it may not vary across observations. The choice set must likewise be fixed. Data may be individual, proportions, or frequencies.

The multinomial probit model will be used in this research to account for the overlap between the alternatives. The choices tree will include 16 alternatives that represent the different routes on the network. However, the number 16 may be changed based on the final database file where 60 subjects will run the simulation.

3.6 Nested Logit Models

One way to relax the homoscedastiticy assumption (i.e., equal variances of distributions of errors) in the multinomial logit model that provides an intuitively appealing structure is to group the alternatives into subgroups that allow the variance to differ across the groups while maintaining the IIA assumption within the group. This specification defines a nested logit model. The nested logit model is currently the preferred extension to the simple multinomial logit discrete choice model. The appeal of the nested logit model is its ability to accommodate differential degrees of interdependence (i.e. similarity) between subsets of alternatives in a choice set. In this section, a general outline of nested logit models is demonstrated.

A nested logit structure allows estimation of proportions among selected sub-modes, prior to the estimation of proportions between modes. For examples, a nested logit model might estimate the proportions of mode choices, such as bus or drive, prior to estimating the proportions of each route to be chosen. This ability of the nested logit model reduces some of the limitations of the multinomial logit model, specially the independence from irrelevant alternatives (IIA) limitation. The nested logit model, first derived by Ben-Akiva (1973), is an extension of the multinomial logit model designed to capture correlation among alternatives. It is based on the partitioning of the choice set C into several nests C_K. Where, for each pair $C_k \cap C_j = 0$. The utility function of each alternative is composed of a term specific to the alternative, and a term associated with the nest. If $i \in C_K$, we have

$$U_i = V_i + \varepsilon_i + V_{Ck} + \varepsilon_{Ck}$$

The error terms ε_i and ε_{Ck} are supposed to be independent. As for the multinomial logit model, error terms (ε_i's) are supposed to be independent and identically Gumbel distributed, with scale parameter σ_k. The distribution of ε_{Ck} is such that the random variable max $j \in C_K$ U_j is Gumbel distributed with scale parameter μ.

In the nested logit model the correlated alternatives are placed in a "nest", which partly removes the IIA property. There is a simple example in Figure 3-1 of the grouping of the alternatives.

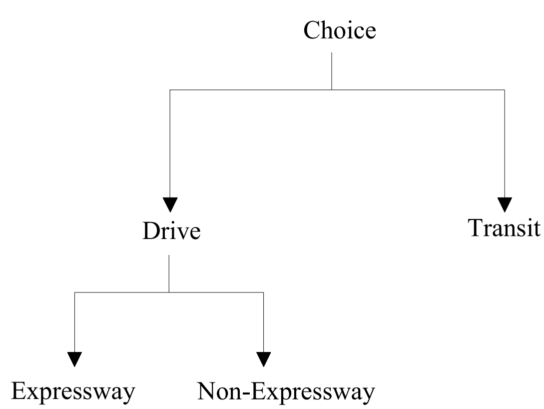

Figure 3-1 An Example for Nested Logit Mode Choice Structure

To fix the idea of a nested logit model, suppose that N alternatives can be divided into M subgroups such that the choice set can be written as: $[n_1,\ldots,n_m]_m$; $m = 1,\ldots,M$ and $\sum_m n_m = N$. This choice-set partitioning produces a nested structure. Logically, one may think of the choice process as that of choosing among M choice sets and then making the specific choice with the chosen set. The mathematical form for a two-nested level logit model is as follows:

$$P_n = P_{n|m} P_m$$

$$P_{n|m} = \frac{\exp(\beta' x_j \mid m)}{\sum_{n_m} \exp(\beta' x_j \mid m)}$$

$$P_m = \frac{\exp(\gamma' z_m + \tau_m I_m)}{\sum_m \exp(\gamma' z_m + \tau_m I_m)}$$

$$I_m = \ln \sum_{n_m} \exp(\beta' x_j \mid m)$$

where P_n is the unconditional probability of choice n, $P_{n|m}$ is the conditional probability of choosing alterative n given that person has selected the choice-set m, P_m is the probability of selecting the choice-set m, $\mathbf{x}_{n|m}$ are attributes of the choices, $\mathbf{z}_m$ are attributes of the choice sets, I_m is called the inclusive value (log sum) of choice-set m, β and γ are vectors of coefficients to be estimated, and τ_m is the coefficient of the inclusive value of choice-set m. If we restrict all inclusive value parameters to be 1, then the nested logit model will be similar to multinomial logit model. The nested logit model is consistent with random utility maximization if the conditions' inclusive value parameter (τ) is bounded between zero and one. The nested logit model has been extended to three and higher levels. The complexity of the model increases geometrically with the number of levels. But the model has been found to be extremely flexible and is widely used for modeling individual choice.

To gain a better understanding of marginal effects of the variables included in a calibrated nested logit model, elasticities can be computed. The direct elasticity formula of an alternative n, which appears in one or more nests, is

$$E_{x_k}^{P_n} = \frac{\partial P_n}{\partial x_k} \cdot \frac{x_k}{P_n} = \frac{\sum_m P_m P_{n|m}[(1 - P_n) + (1/\tau_m - 1)(1 - P_{n|m})]}{P_n} \beta_k X_k$$

where E represents the direct elasticity, P_n is the probability of a person to chose mode n, P_m is the probability of nest m, X_k is the variable being considered to have an effect on mode n, and β_k is the estimated coefficient corresponding to the variable X_k. The terms in the summation evaluate to zero for any nest that does not include alternative n. The elasticity reduces to multinomial logit elasticity, $(1-P_n)\beta_k X_k$, if the alternative does not share a nest with any other alternative or is assigned only to nests for which the inclusive-value parameter (τ) equals one.

CHAPTER 4

OTESP DESCRIPTION

4.1 OTESP: An Overview

Orlando Transportation Experimental Simulation Program (OTESP) is a powerful interactive computer simulation tool. This simulation is developed in this project to enable us to run a subject through several scenarios on his/her morning trips from the origin (assumed-home) near the intersection of Semoran (436) and Lack Underhill Dr. to the destination at the University of Central Florida (UCF), where the subjects work or go to school. A portion of the Orlando network has been captured from a GIS database. The chosen network consists of 25 nodes and 40 links representing the available network from OTESP origin to its destination. Figure 4-1 shows this network, its origin, its destination, and the coded numbers for all links and nodes.

This realistic network has been chosen for this research as it has different types of highways. For example, E. Colonial (SR 50) represents a typical urban arterial road with signalized intersections approximately every 1-mile. University Blvd. and Lake Underhill Dr. (2-lane rural design) represent less urbanized roads than E. Colonial. E-W expressway (SR 408) and Greeneway (SR 417) are two toll expressways in the OTESP network. There are, also, six roads in the network that represent the north-south links (Semoran (SR436), Goldenrod (SR 551), N Dear rd., Rouse rd., Alfaya Trl., and Libra-Discovery Dr.).

Table 4-1 presents the OTESP network links with the realistic distance, speed limit, and free flow travel time for each link. Subjects are required to run a serious of 10 simulated weekdays (AM only) from their assumed home to their work/school at UCF.

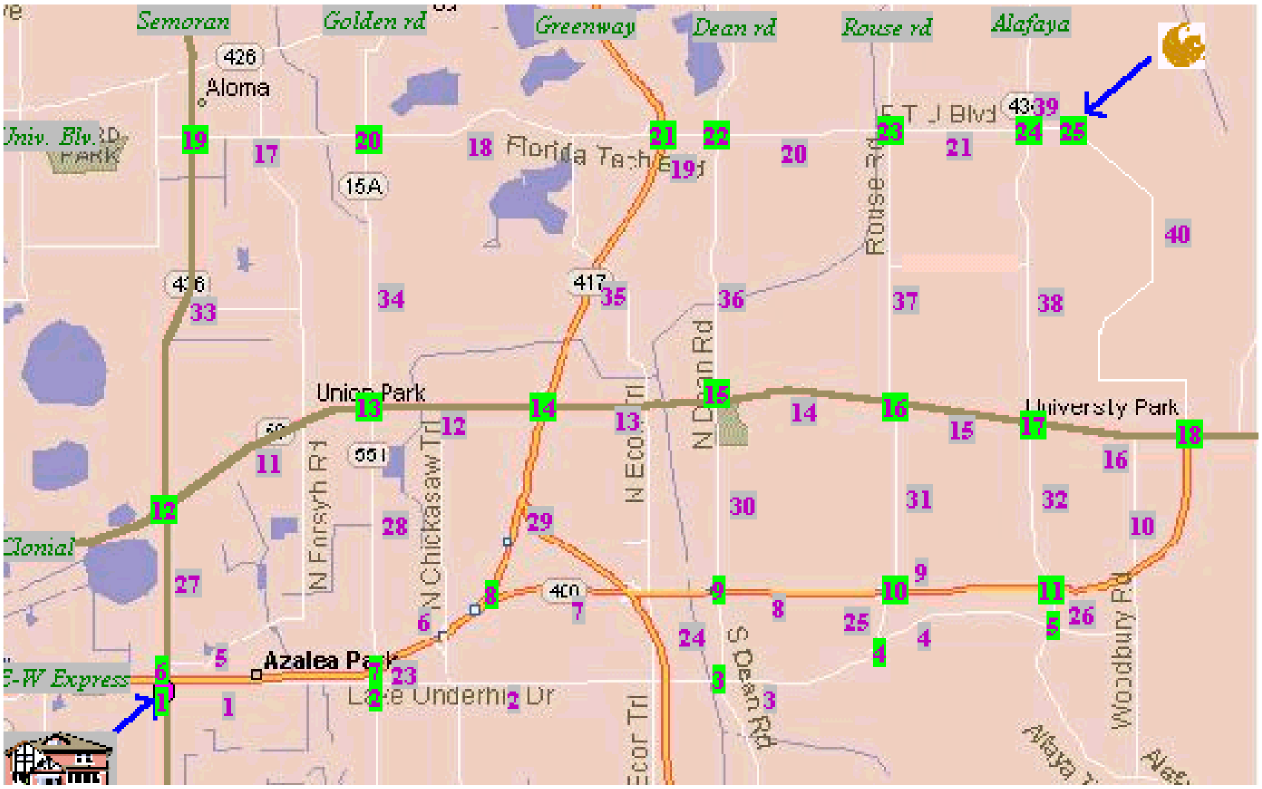

Figure 4-1 Codes for links and nodes posted on the OTESP's map

4.2 Components of the OTESP

4.2.1 "Welcome" Form

The simulation starts with a welcome screen that welcomes the subject. This screen says "Thank you for participating in the Orlando Transportation Experimental Simulation Program (OTESP)".

4.2.2 "Introduction" Form

This screen is designed to introduce the simulation to the subjects. It has a brief summary of the objectives, network size, description of the requirements from a subject, and information provided for each driving scenario. The wording of OTESP introduction screen is shown in Figure 4-2. A push-button captioned "*Click on me after reading the above screen carefully*" at the bottom of this form transfers the subject to the next form.

4.2.3 "Personal Information" Form

After reading the "*Introduction*" form. Subjects are presented with "*Personal Information*" screen (see Figure 4-2) in which they are required to answer some personal questions in the form of pull-down menus, combo boxes, text boxes, and option boxes (radio buttons). Some of these questions are designed to recognize how familiar is the subject with the ATIS for both pre-trip and en-route information. For example, the simulation asks the subject about his/her likelihood of using traffic information either before taking the trip or while driving. Other questions, enabled only if the subject said that he has used traffic information, ask about how and how frequently does the subject receive these types of information before and while driving.

Table 4-2 summarizes these questions and the available choices in their pull-down menus. At the bottom of this screen, there are two push buttons captioned "*Back to the Introduction Form*" and "*Start*". The fist one allows the subject to retune back to the "*Introduction*" form while the second takes the driver to the next form.

Table 4-1 OTESP Network Links

Link Number	Road Name	Distance (mi)	Speed Limit (mph)	Free Flow Travel Time (min.)
1	Lake Underhill Dr	1.52	35	2.61
2	Lake Underhill Dr	1.94	50	2.33
3	Lake Underhill Dr	1.24	50	1.49
4	Lake Underhill Dr	1.31	50	1.57
5	E-W Express 408	1.52	65	1.40
6	E-W Express 408	0.90	65	0.83
7	E-W Express 408	1.77	65	1.63
8	E-W Express 408	1.24	65	1.14
9	E-W Express 408	1.17	65	1.08
10	E-W Express 408	1.79	65	1.65
11	Colonial Dr. (SR 50)	1.71	50	2.05
12	Colonial Dr. (SR 50)	1.25	50	1.50
13	Colonial Dr. (SR 50)	1.27	50	1.52
14	Colonial Dr. (SR 50)	1.28	50	1.54
15	Colonial Dr. (SR 50)	1.00	50	1.20
16	Colonial Dr. (SR 50)	1.14	50	1.37
17	University Blvd.	1.26	45	1.68
18	University Blvd.	2.27	45	3.03
19	University Blvd.	0.40	45	0.53
20	University Blvd.	1.23	45	1.64

Link Number	Road Name	Distance (mi)	Speed Limit (mph)	Free Flow Travel Time (min.)
21	University Blvd.	1.00	45	1.33
22	Semoran (436)	0.04	50	0.05
23	Goldenrod. (551)	0.09	50	0.11
24	N Dean Road (425)	0.62	45	0.83
25	Rouse Road	0.38	50	0.46
26	S Alfaya Trl. 434	0.28	45	0.37
27	Semoran (436)	1.24	50	1.49
28	Goldenrod. (551)	1.91	50	2.29
29	Greeneway (417)	1.58	65	1.46
30	N Dean Road (425)	1.44	45	1.92
31	Rouse Road	1.36	50	1.63
32	S Alfaya Trl. 434	1.25	45	1.67
33	Semoran (436)	1.79	50	2.15
34	Goldenrod. (551)	2.76	50	3.31
35	Greeneway (417)	1.99	65	1.84
36	N Dean Road (425)	2.20	45	2.93
37	Rouse Road	1.94	50	2.33
38	S Alfaya Trl. 434	2.94	45	3.92
39	University Blvd.	0.40	25	0.96
40	Libra - Discovery Dr.	3.74	35	6.41

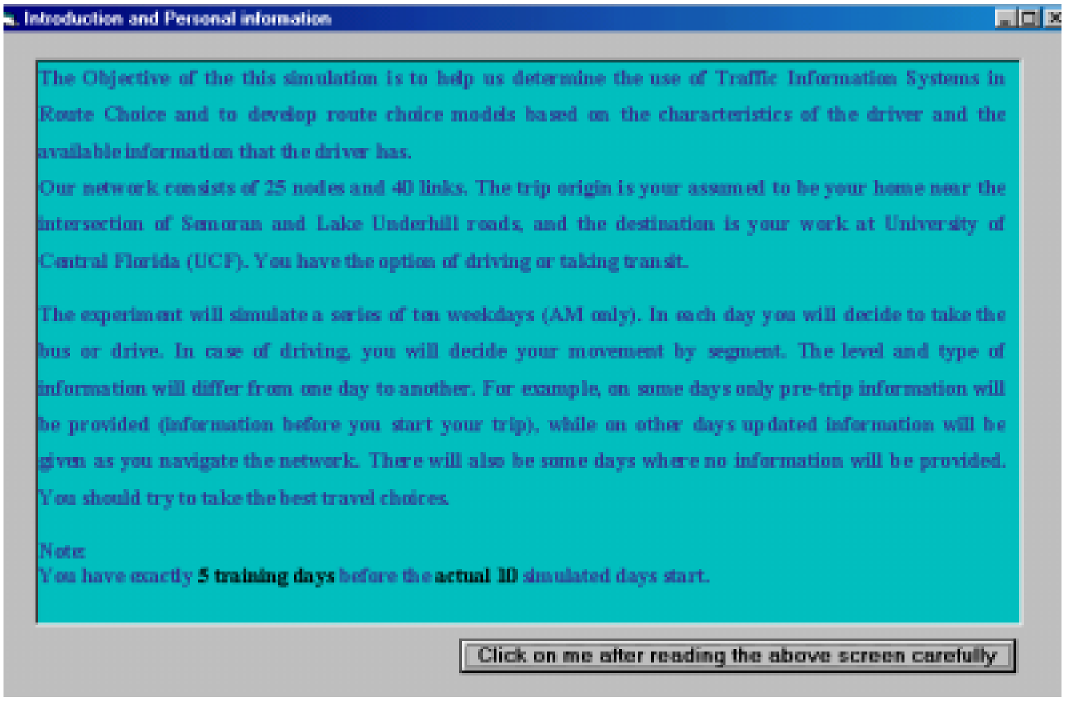

Figure 4-2 OTESP "Introduction" screen

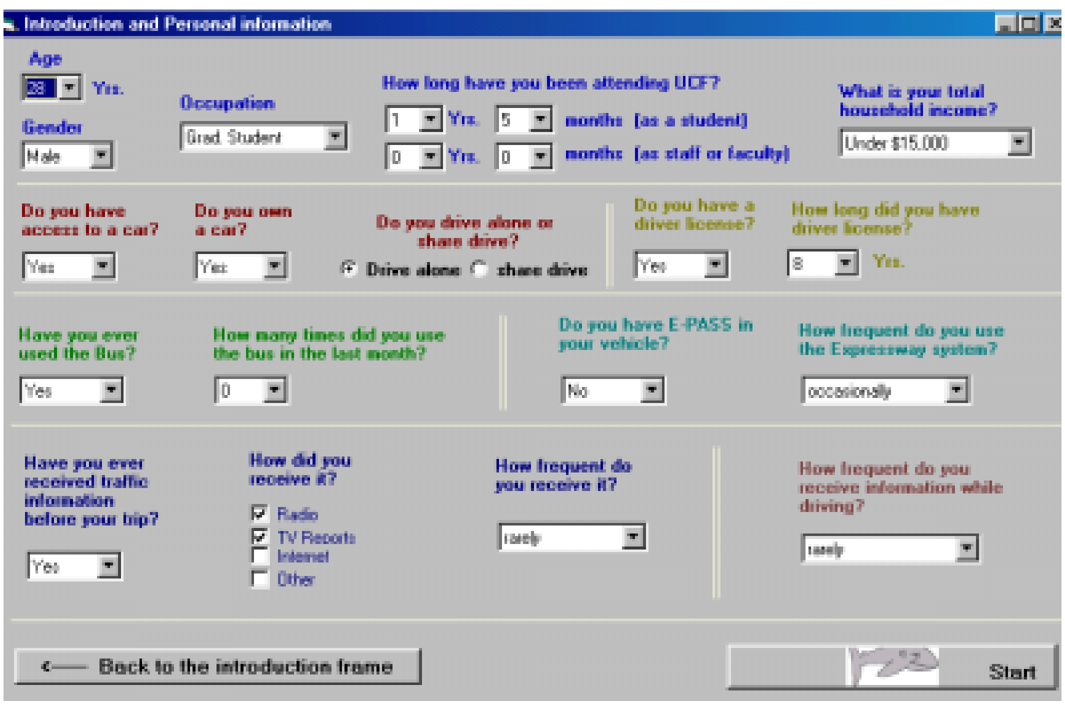

Figure 4-3 OTESP "Personal Information" screen

Table 4-2 OTESP "Personal Information" Form's questions.

Number	The asked question	Object type	Available choices	Remarks
1	Age	Text box	NA	
2	Gender	Combo box	1- Male 2- Female	
3	Occupation	Combo box	1- Faculty 2- Staff 3- Grad. Student 4- U. Grad. Student 5- Other	
4	How long have you been attending UCF as a student?	Text box	NA	
5	How long have you been attending UCF as a faculty?	Text box	NA	Enabled only if question #3's answer is Faculty or Staff or other
6	What is your total household income?	Combo box	1- Under $15,000 2- $15,000 to 24,999 3- $25,000 to 34,999 4- $35,000 to 49,999 5- $50,000 to 64,999 6- $65,000 to 80,000 7- Over $80,000	
7	Do you have access to a car?	Combo box	1- Yes 2- No	
8	Do you own a car?	Combo box	1- Yes 2- No	Enabled only if question #7's answer is Yes
9	Do you drive alone or share drive?	Option box	1- Drive alone 2- Share drive	Enabled only if question #7's answer is Yes
10	Do you have driver license?	Combo box	1- Yes 2- No	
11	How long did you have driver license?	Text box	NA	Enabled only if question #10's answer is Yes
12	Have you ever used the Bus?	Combo box	1- Yes 2- No	
13	How many times did you use the bus in the last month?	Text box	NA	Enabled only if question #12's answer is Yes
14	How frequent do you	Combo box	1- Every day	

Number	The asked question	Object type	Available choices	Remarks
	use the Expressway system?		2- Occasionally 3- Rarely 4- Never	
15	Do you have an E-PASS in your vehicle?	Combo box	1- Yes 2- No	Enabled only if question #14's answer is Yes
16	Have you ever received traffic information before your trip?	Combo box		
17	How did you receive it?	4 check boxes	1- Radio 2- TV Reports 3- Internet 4- Other	Enabled only if question #16's answer is Yes
18	How frequent do you receive it?	Combo box	1- Every day 2- Occasionally 3- Rarely	Enabled only if question #16's answer is Yes
19	How frequent do you receive information while driving?		1- Every day 2- Occasionally 3- Rarely 4- Never	

4.2.4 "Normal Route" Form

The objective of this form is to let the analyst know the link-by-link itinerary that the subject takes on a morning-week-day trip from home to work. A help frame, labeled "*Please, Read Carefully*" appears in the first time of loading this form, and instructs the subjects to correctly choose their link-by-link normal route. A push button captioned "*Click here after reading carefully*" puts this form out of sight and allows the subject to start choosing the preferred road. At each time the subject clicks on any link, its color changes to be magenta and its check box changes to be marked. The form, shown in Figure 4-4, also includes three push buttons as follows:

1. The first button, labeled "*Show all available intersections*", is designed to let the subjects know the available intersections on the network. By clicking on this button, small green-solid circles appear at all the available intersections.
2. The second button, labeled "*Help*", allows the subject to read the instructions of this form appearing in a separated frame in the center of the current form. Subjects can come back to the "*Normal Route*" form by clicking on a button labeled "Click here after reading carefully"
3. The third button, labeled "*Start the simulation*", is designed to transfer the subject to the "*Simulation*" form after coding and writing the chosen links of the subject's normal-route into the built-in database file.

Figure 4-5 shows the "*Normal Route*" form without the previous instruction frame. It also shows an example of an itinerary from the origin to the destination going east through the E-W Expressway (408) then north Alafaya Trl. and finally University Blvd. to the destination.

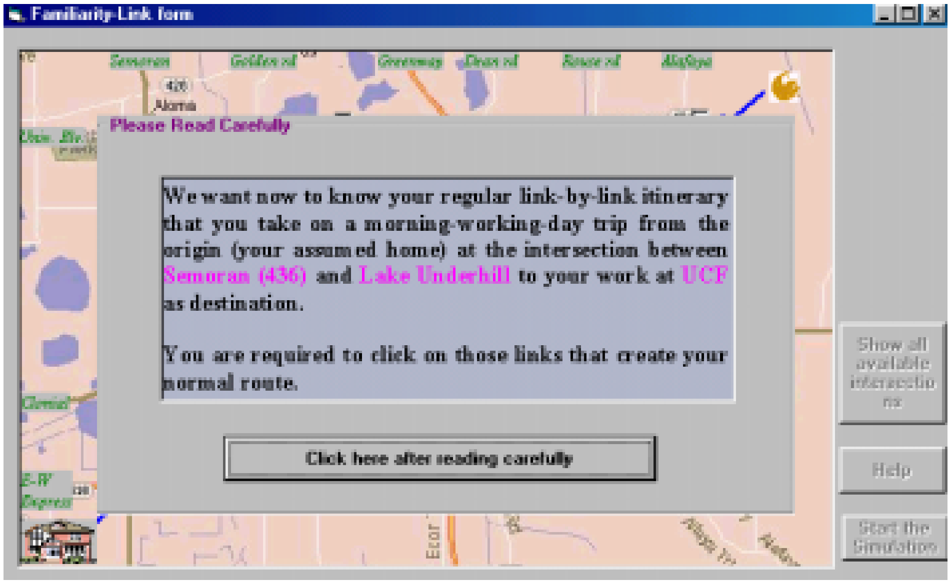

Figure 4-4 OTESP "Normal Route" form with the instruction frame

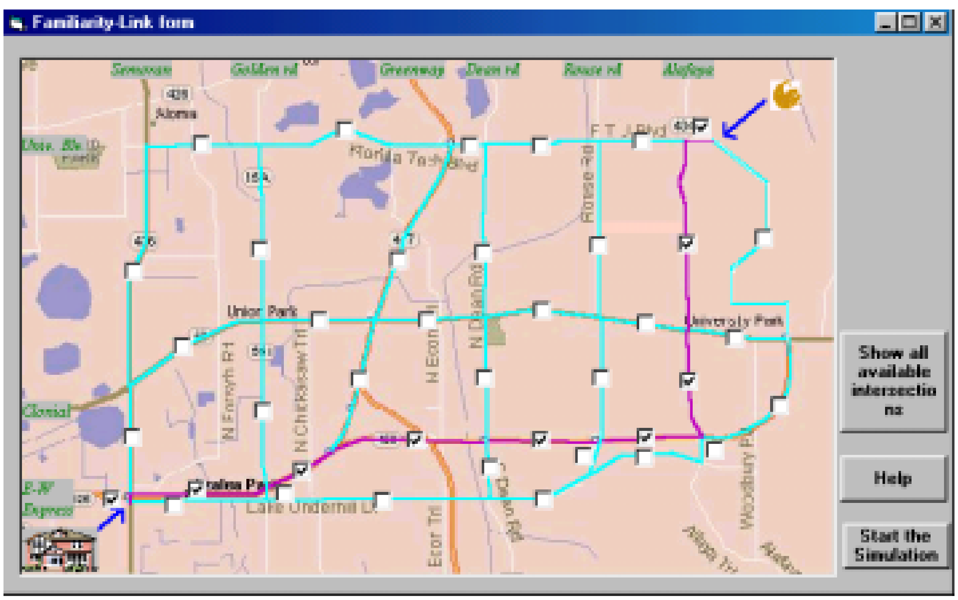

Figure 4-5 OTESP "Normal Route" form without the instruction frame

4.2.5 "Simulation" Form

The "*Simulation*" form is the main form in OTESP. It simulates a package of 15 bus/drive trial days using a powerful, interactive, and easy-user interface. The simulation has several travel scenarios, in which the subject is required to make mode and route choices in the existence of ATIS. Figure 4-6 shows the available mode choices at the beginning of each day. Different levels of information are provided to the subjects including no information, pre-trip information, and en-route information. Information is provided with and without advice for both transit and drive choices. The subject makes different travel choices while driving on the network. Different levels of congestions are also provided in this simulation. This section presents design and methodology of the traffic information and advice provided to the subjects and the logic behind each.

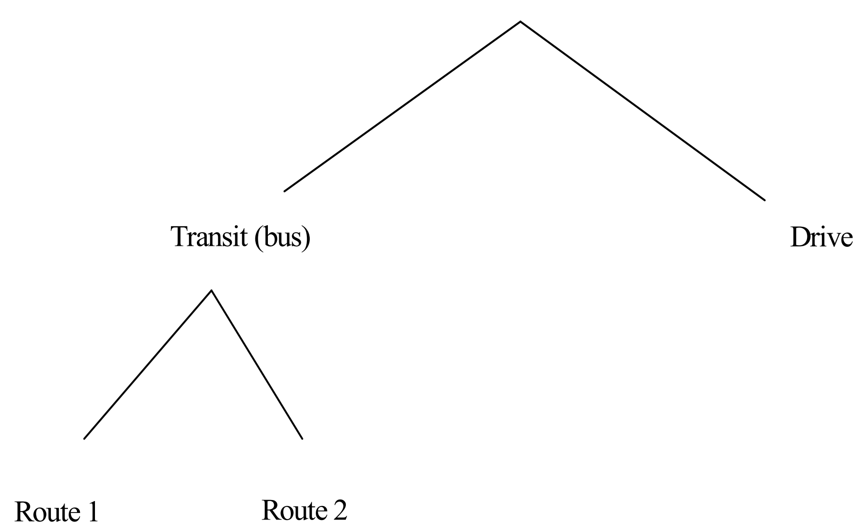

Figure 4-6 Available modes in the beginning of each simulated day

4.2.5.1 OTESP Information

The “Simulation” form presents pre-trip and en-route traffic qualitative and quantitative information and advice to the subjects for both drive and transit. The next four sections introduce these types of information.

4.2.5.1.1 Information Before Mode Selection

Pre-trip information for both drive (private car) and transit (the two bus routes) are presented inside the simulation in the form of (see Figure 4-7):

1. Expected total travel time on bus route one, randomly generated according to a Normal (30,6) distribution, truncated so it gets bigger than or equal to 0.85 μ (25.5 minutes).
2. Bus route one fare of $1.00, fixed for all trial days;
3. Expected total travel time on bus route two, randomly generated according to a Normal (40,3) distribution, truncated so it gets bigger than or equal to 0.85 μ (34.0 minutes).
4. Bus route one fare of $0.75, fixed for all trial days; and
5. The expected total travel time on the network using a private car, randomly generated according to a Normal (20,5) distribution, truncated so it gets bigger than or equal to 0.85 μ (17 minutes).

4.2.5.1.2 Driving Information After Mode Selection

OTESP presents a complete view of the current situation on the network in the form of quantitative and qualitative information as follows:

1. *Quantitative information*: travel time for each single link on the network including the link that has an incident.

2. *Qualitative information:* All the network's links are colored by different four colors:
    a. *Green,* for free flow links;
    b. *Yellow,* for moderate links;
    c. *Red,* for congested links*; and*
    d. *Blue,* for links that form together the advised route that has the minimum travel time on the network at that time.

All the above information are updated each time the simulated car reaches an available intersection on the network.

4.2.5.1.3 Simulated Car Speed

The moving car/bus is simulated in the OTESP by a circular object. This simulated car moves on the network's map according to a separated visual basic code that is designed and written to have a two-dimensional coordination system for the map. However, this system of coordinates allows the program to move the simulated car freely and easily along a link (curve, straight, or combined) until the simulated car reaches the end of this link. As mentioned above, the subject is required to make a decision at every intersection using the curser and the giver four directional-arrows.

A separated code, also, is written to control the speed of the simulated car. This simulated speed changes based on the congestion level of each link so as the subject can easily recognize the congestion of the link that he/she passing through.

4.2.5.1.4 Route Advice

OTESP presents an advised route to the drivers in the form of blue-links from the current position of the simulated car to the destination (see Figure 4-10 and Figure 4-12). The advised route is calculated based on Moors shortest path algorithm (Pallottino et al., 1998). Section 4.2.5.5 presents this method in detail.

4.2.5.1.5 Crash Location

The simulation presents one crash on a random link on each trial day. The crash will remain in its place until the end of that day. A small picture shows two collided cars will be posted near the link where the incident so as the driver can easily recognize that this link has a crash. A driver is still able to pass through the crash link. But, once the simulated car enters a link the driver has no choice but to continue moving to the end of this link. A label box has the travel time in minutes will be shown near the crash link and the color of this link will be red. The crash location is chosen based on a uniform distribution for the 40 links of the network. The crash link is forced to be in the expressway links number 6, 20, and 35 for the trial day's number 3, 10, and 13 respectively to divert the advised minimum-travel-time route from the expressway links. While the chosen crash link remains random for the other 12 days.

4.2.5.2 Five Different Scenarios

OTESP presents pre-trip and en-route traffic qualitative and quantitative information to the subject in five different scenarios (see Figure 4-8 through Figure 4-12 for different scenarios):

1. *Trial days with no information*. In this scenario the subject is required to run the simulation without information given to him. He/She can either take one of the two bus

routes or drive. In case of driving, the subject is required to make the next moving decision once he/she reaches an available intersection on the network. The subject is given the cumulative total travel time and the toll cost or fare cost from the origin to the current position for both drive and transit modes.

2. *Trial days with pre-trip information and without advice*. Both transit and drive information are provided before the subjects start moving. First, the two bus routes travel times and fares are provided in addition to the expected minimum travel time on the network in the case of driving. Second, if the subject chooses "drive" he will also be given qualitative and quantitative pre-trip information on the network for that time (see section 4.2.5.1.2 above). This information disappear after he/she begins the trip.

3. *Trial days with pre-trip information and advice*. Similar to the second scenario but the subject will be given a pre-trip advice for the shortest path route from the origin to the destination.

4. *Trial days with both pre-trip and en-route information and without advice*. Similar to the second scenario except that the information will remain displayed until he/she reaches the destination.

5. *Trial days with both pre-trip and en-route information and advice*. Similar to the fourth scenario except that subjects are given an advice for the shortest path route from the current position of the simulated car to the destination.

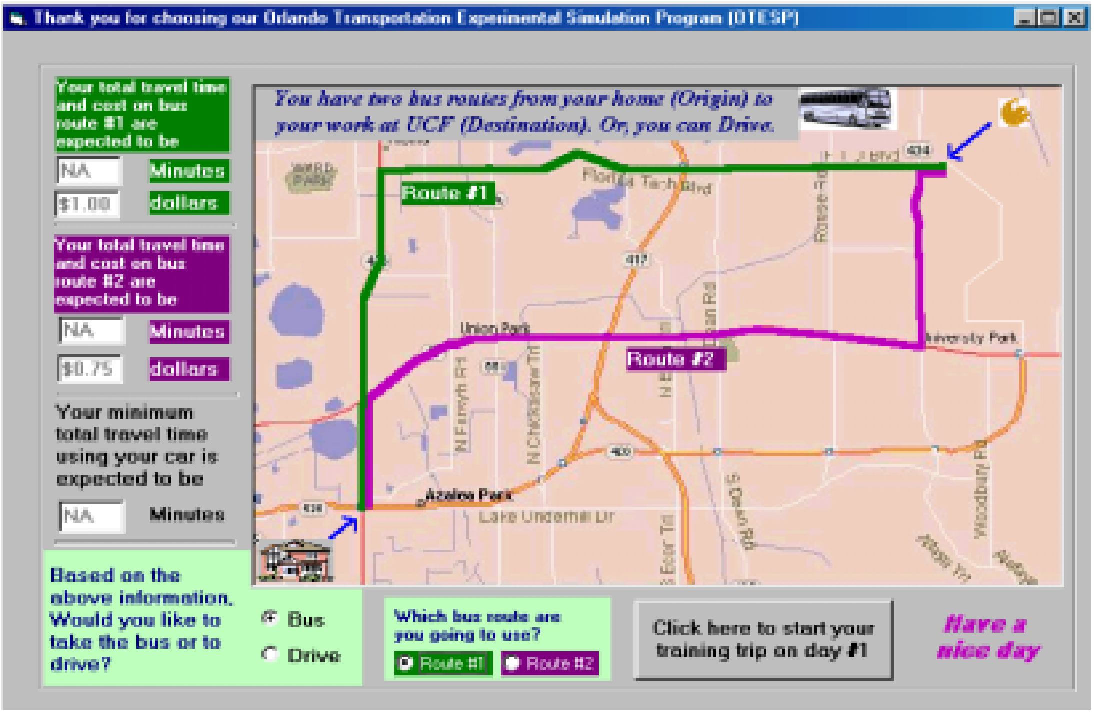

Figure 4-7 "*Mode Choice*" Form

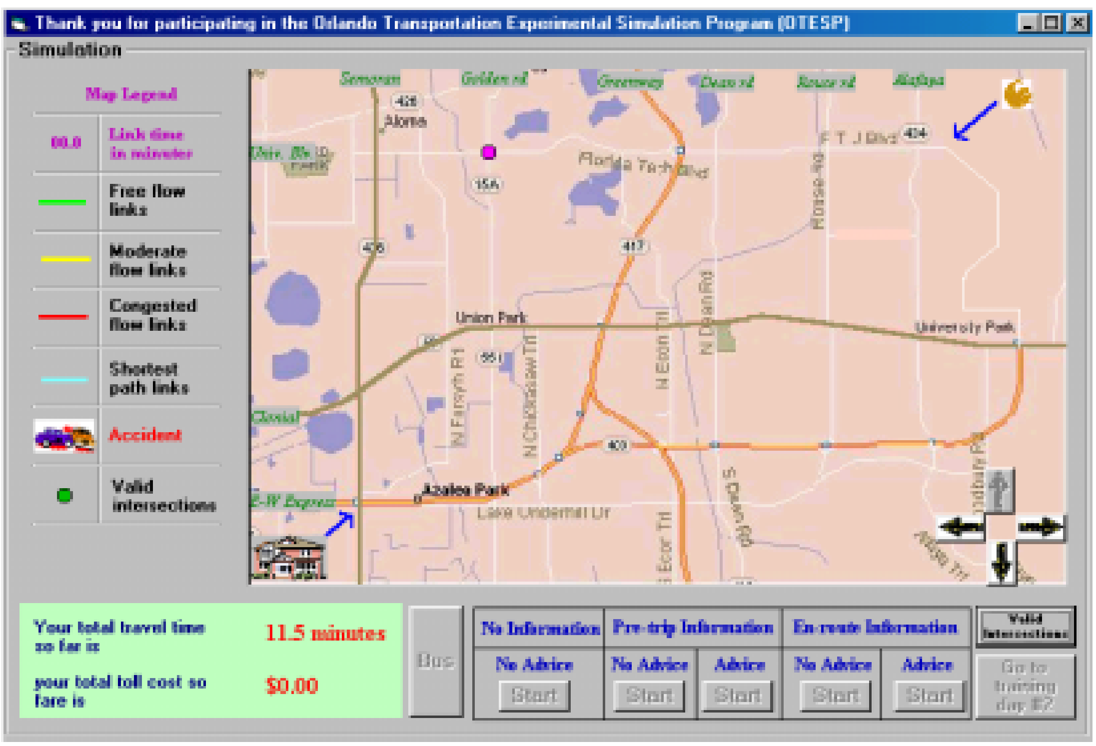

Figure 4-8 Scenario #1

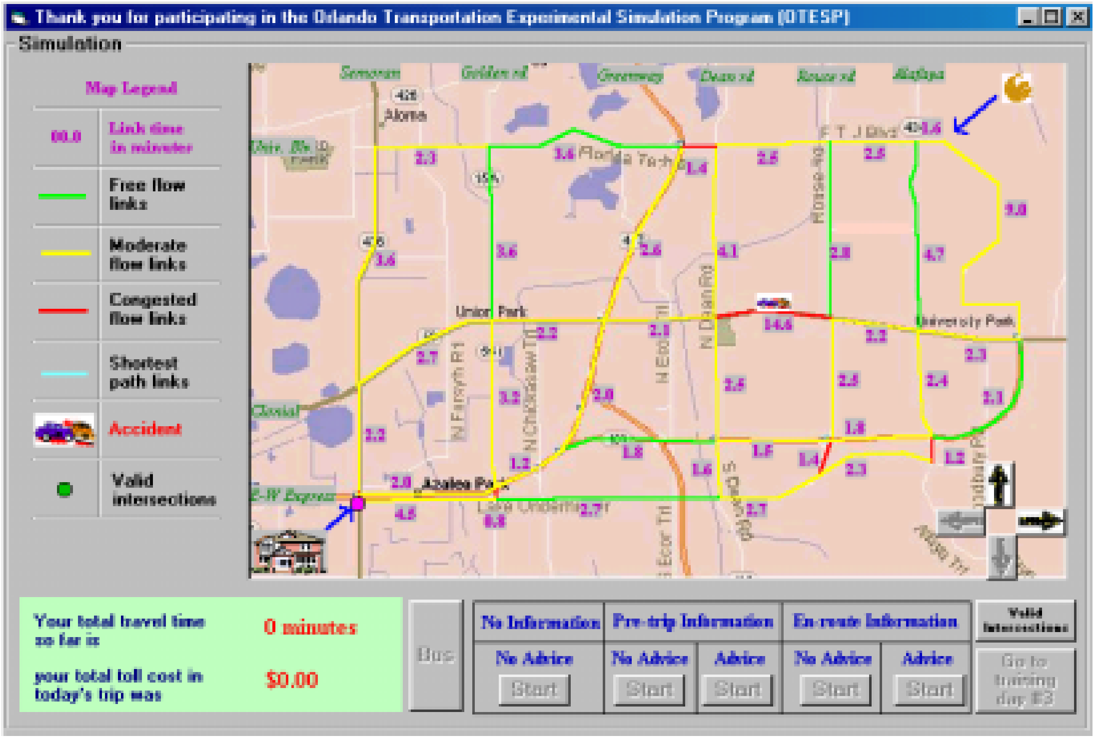

Figure 4-9 Scenario #2

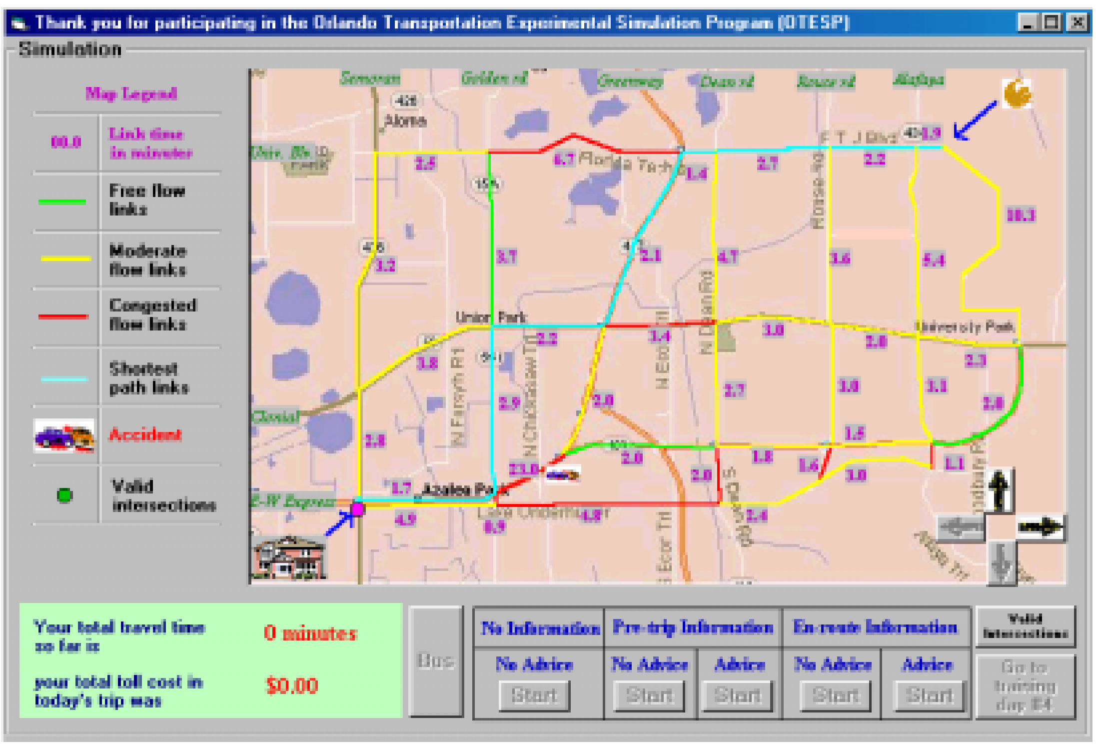

Figure 4-10 Scenario #3

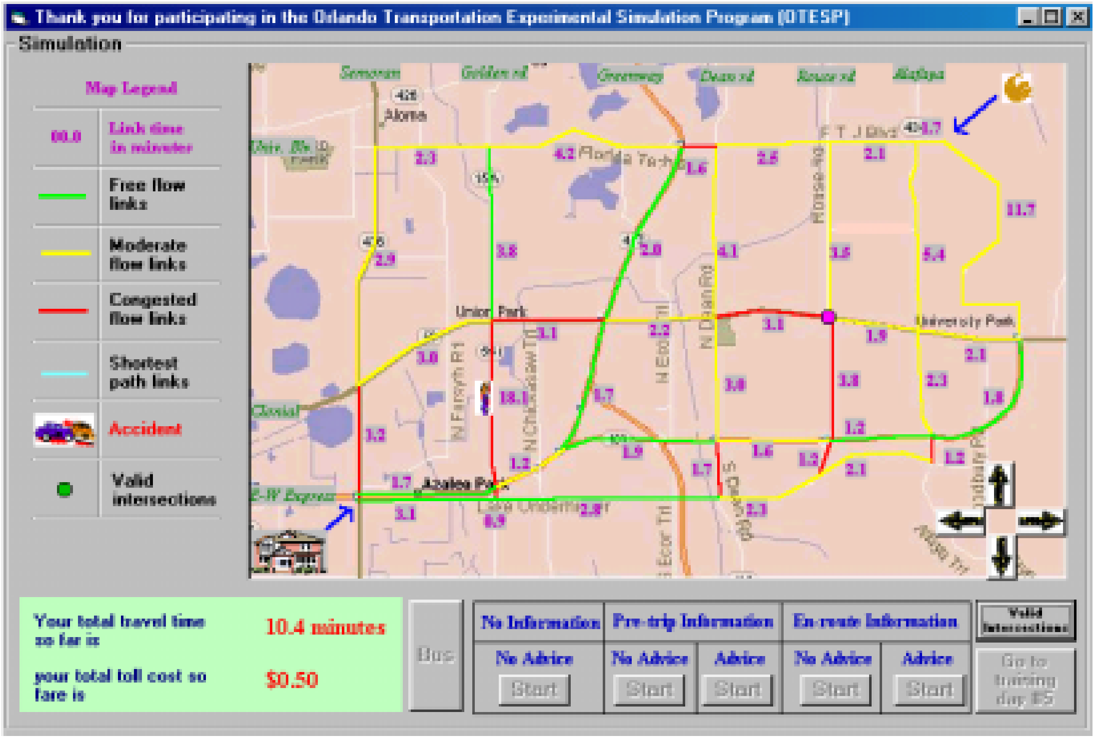

Figure 4-11 Scenario #4

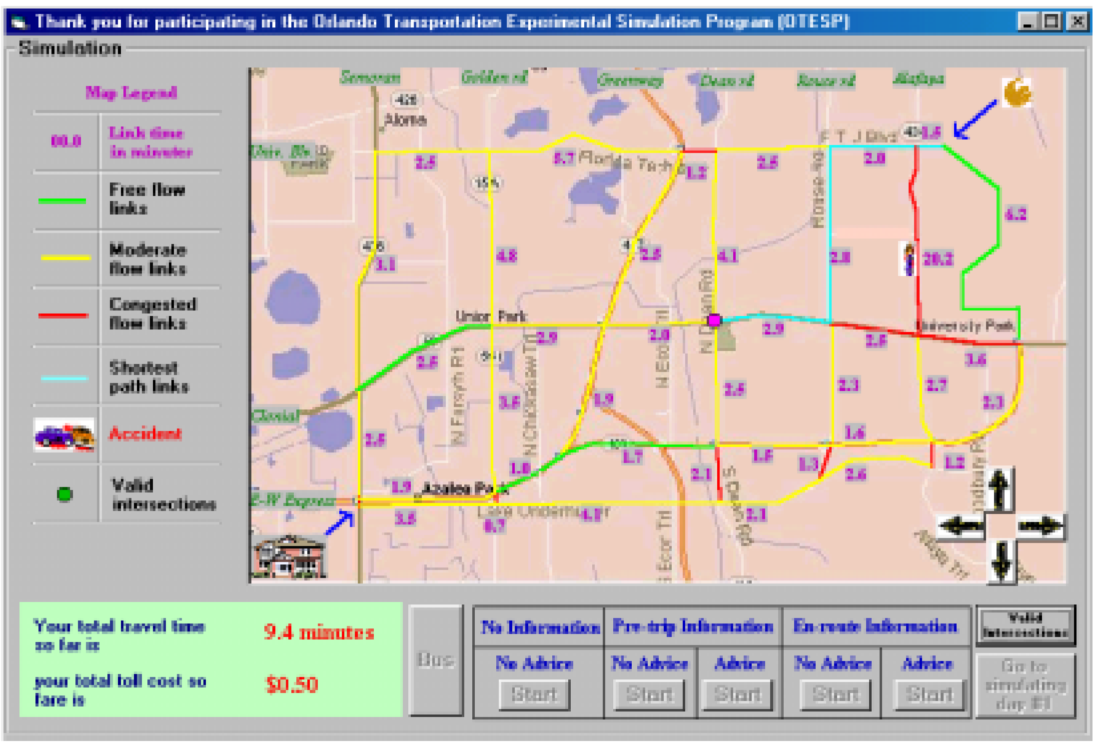

Figure 4-12 Scenario #5

4.2.5.3 Travel Time Computations

This section explains how the travel time of each link is computed and generated interactively. Travel times on all links update after each single movement of the simulated car or after any choice done by the subject. The travel time on a given link is randomly generated according to a Normal (μ,σ) distribution, truncated so it gets bigger than or equal to 0.85 μ (see Figure 4-13). The mean, μ, is the free flow travel time T_{ff} for each link.

Different standard deviations are chosen for different links depend on the actual criteria for each link as follows:

1. Standard deviation of value (0.2*μ) is chosen for the Expressway links.
2. Standard deviation of value (0.5*μ) is chosen for the Colonial Dr. links representing the high level of congestion usually experienced on that route.
3. Standard deviation of value (0.35*μ) is chosen for all other links.

The standard deviation of each link is a function of its free flow travel time T_{ff}. However, there is a large variation in the free flow travel times because of the variation of the distances and speed limits between the links. For example, a fixed standard deviation value might be reasonable for one link but unreasonable for the other link in the same route or under the same characteristics and circumstances. Hence, the standard deviation for all links is normalized by their free flow travel times. Finally, each link has its own fixed μ and σ.

For Signalized intersections, A random value $T_{sig.}$ is added. This value is randomly generated according to a Normal (41,15) distribution (see Schooley, 1992).

There is one incident on the network on each trial day. The incident represents non-recurring cause of delay. The travel time for the incident link is randomly generated according to a Normal

(20,5) distribution, truncated so it gets bigger than or equal to 0.85 μ (17 minutes). A crash icon is displayed at the location of the incident. Standard deviation (σ) of 5 minutes, one forth of μ, is chosen in this case to represent a high variation in the travel time of the incident link.

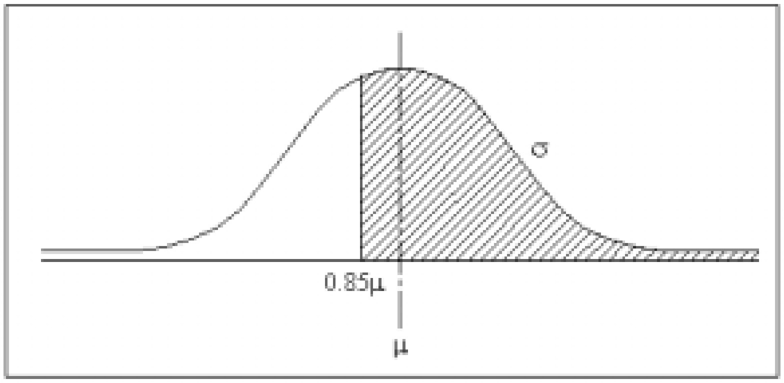

Figure 4-13 Truncated N (μ,σ) for travel time computations

4.2.5.4 Toll Plazas Delay Computations

OTESP network has two main toll plazas one located on the E-W expressway (SR 408) between Rouse and Dean roads called DEAN Toll Plaza. The other one located on the greenway (SR 417) between Colonial and University Blvd called University plaza. Each plaza, after installing the Electronic Toll Collection (ETC) technology known as E-PASS, has three methods for toll collection:

- Manual lanes;
- Automatic coin machine lanes; and
- E-PASS lanes.

The average queuing delay for peak periods is 40 seconds (Mohammed, 2000). Add a service time (about 5 seconds) to the average queuing delay to get a rough estimate of the average idle time (45 seconds). Also, from Al-Deek (2001) and using field data conducted on Tuesday June 6, 2000 from 7:00am to 8:00am (5-minutes intervals), the maximum average queuing delay was 39 seconds. Also, the study found that there is no significant difference in the distributions for maximum queuing delay for both manual and automatic coin machine lanes. EPASS vehicles have no significant delay.

OTESP computes a toll delay of a random number generated according to a {N (40,5.5) + 5} for NON-EPASS vehicles and zero for EPASS vehicles. A standard deviation of 5.5 seconds is chosen based on field data by (Al-Deek, 2001). In this simulation, EPASS drivers will be shown a window says, "*You are passing through an EPASS lane*" (see Figure 4-14) and disappears automatically after a limited time (2/5 of the total link simulated travel time) while no additional travel time will be added. In the other side, NON-EPASS vehicles will be stopped for a limited time (equal to a simulated 5 seconds) with a window saying "*You are paying the Toll*" and an additional travel time will be added based on the above equation. Using the "*personal information*" form (see section 4.2.3), the simulation recognizes if the subject has an E-PASS system in his vehicle or not by loading the coded integer value in the 19th field of the "*Personal Information*" table. This filed has the binary subject's answer to a question says "Do you have E-PASS in your vehicle?".

Figure 4-14 Delay caused by Toll Plazas

4.2.5.5 Shortest Path Computations

Shortest Path problems are among the most studied network flow optimization problems, with interesting applications in various fields. One such field is transportation, where shortest path problems of different kinds need to be solved. Minimum path algorithm is relatively time consuming calculations especially when a number of links and nodes of a network is large. A quantity of calculation for this algorithm increases proportional to a factorial of the number of elements. Shimazaki et al., (1988) analyzed the shortest path algorithm used by a person from a cognitive psychological point of view, and developed a computer program which simulates the algorithm of the person.

Moore algorithm (Pallottino et al., 1998) is chosen in the OTESP process to present the advised route to the subject from the origin to the destination in the pre-trip advice scenario. It also presents the advice from the current position to the destination while the driver is moving on the network for the en-route advice scenario. Moore's algorithm is chosen because it is the most widely used algorithm. This algorithm does not require all possible routes between an origin and the destination to be individually investigated to find the shortest route. Rather, a minimum "tree" is developed by fanning out from the origin to all other accessible nodes in increasing order of their travel times summation from the origin. A tree is defined as the set of shortest routes from an origin to all other points in the network.

A visual basic code is developed inside the simulation capturing the above technique to advise the driver to take the calculated shortest path based on the travel time. The shortest path appears on the map while the driver is moving as blue links from the current position of the simulated car to the destination (see Figure 4-12). As all other features of the simulation, the shortest path calculations and link-color adjustments are done every time the driver takes a decision to move form one intersection to another.

4.2.5.6 Toll Cost Computations

The realistic locations and toll amounts (two-axle cars) for main, entrance, and exit toll plazas on OTESP network have been identified and considered by the simulation. So, while the simulated car moves on the network, the cumulative toll cost is calculated and given to the driver. As the other features of OTESP, a dedicated visual basic code is written to map up all toll plazas locations and add their toll amounts to the total toll cost value given to the subject (whether main or ramp plazas).

4.2.5.7 OTESP Simulated Days

Before the beginning of the 10 simulated days, subjects are required to run 5 training days to help them have better understanding about the system and to be familiar with it. It is very important for us to train the subjects on how they can correctly make the required decisions because the simulation has many menus, message boxes, text boxes, labels, and push buttons. The number five here is chosen to allow each subject run a trial day for each travel scenario.

In each simulated day, the subject travels from the origin to the destination using two forms. The first form, labeled "*Mode Choice",* allows the subject to either take the bus or drive. While the other form, labeled "*Travel*", allows the subject to move the simulated car on different segments of the network using the arrow keys of the keyboard or by using the computer mouse. "*Mode Choice" and* "*Travel*" forms are discussed in details hereinafter.

4.2.5.7.1 "Mode Choice" Form

In the beginning of each simulated day, the subject is presented by the "*Mode Choice*" form (see Figure 4-7). This form has the two bus routes in addition to the drive option. Based on the given information to the subject in this form, he/she chooses to either take the bus (route one or two) or drive in his/her morning trip from the specified origin to the specified destination. The first bus itinerary starts north through Semoran (436) all the way then east University Blvd until the destination, passing through 9 links from OTESP network (link22, 27, 33, 17, 18, 19, 20, 21, and 39). The second bus itinerary starts north through Semoran (436), turns right onto Colonial (50) east, turns left onto north Alafaya Trl (434), and finally right onto Gemini to the destination. The second bus route passes through 9 links from OTESP network (link 22, 27, 11, 12, 13, 14, 15, 38, and 39). Route1#1 links take the green color while route #2 take the magenta color (see Figure 4-7).

"*Mode Choice*" form has the following:

1. Expected total travel time on bus route #1, calculated based on a Normal (30,6) distribution, truncated so it gets bigger than or equal to 0.85 μ (25.5 minutes). Given in all scenarios except the first one;
2. Bus route #1 fare of $1.00, fixed for all trial days;
3. Expected total travel time on bus route #2, calculated based on a Normal (35,3) distribution, truncated so it gets bigger than or equal to 0.85 μ (29.75 minutes). Given in all scenarios except the first one;
4. Bus route #2 fare of $0.75, fixed for all trial days. Therefore bus route #1 is generally faster with higher travel time variation and fare. Route #2 is the opposite;

5. The expected total travel time on the network using a private car, calculated based on a Normal (25,5) distribution, truncated so it gets bigger than or equal to 0.85 μ (21.25 minutes). Given in all scenarios except the first one.
6. Two radio buttons in one sub-frame labeled “Bus” and “Drive” allow the subject to choose either to take transit or drive.
7. Two radio buttons in one sub-frame, enabled only if the driver chooses the “Bus” button in the previous sub-frame, labeled “Route #1” and “Route #2” allow the subject to choose either route #1 or route #2.
8. At the end of this form, there is a push button that transfers the interface to the travel form. This button has a dynamic label, i.e., its label changes every trial day. For example, in the training day #3 the label will be “*Click here to start your training trip on day #3*”.

4.2.5.7.2 “Travel” Form

The subject travels in this form from the origin to the destination. Four directional-arrow buttons move the simulated car through the network. This form has the following:

1. A network map. This map has 40 text boxes represent the 40 links’ travel times, one crash at a random link. Also the colors of all links are changeable to represent the congestion level as discussed hereinafter.
2. Map legend
3. Six push buttons, one for the bus and 5 for the different 5 scenarios. Only one is enabled on each day.
4. Four directional-arrow buttons allow the driver to move the car on the network from one intersection to another. Only the available directions’ arrows will be enabled at each

intersection. For example, the north button will be disabled for the University Blvd intersections (see the map).

5. A button labeled "*Valid Intersections*" is designed to draw small dots at all the available intersections on the network. These dots show the driver the locations where he is required to make a decision.
6. At the end of this form there is a push button that ends the current trial day and moves the subject to the next day. This button has a dynamic label, i.e., its label changes every trial day. For example, at the end of training day #2 the label will be "*Go to training day #3*".
7. A label displays the total travel time in minutes that passed since the beginning of each trial day. This value will be updated every movement. At the end of the day, it provides the total experienced travel time representing the feedback.
8. A label displays the total toll cost in dollars paid on the Expressway links since the beginning of each trial day. This value will be updated every movement. At the end of the day, it provides the total experienced toll representing the feedback.

4.2.6 "Feedback" Form

At the completion of the simulation experiment, subjects will be asked some questions related to their experiences with the simulation. These questions rate the subjects' perceptions of the importance of the information given to them, subjects' willingness to purchase an information system, and potential price they might be willing to pay for such a system. "*Feedback*" form (Figure 4-15) is designed to capture these questions. The wording of these question and the possible choices is given in given in Table 4-3. "*Feedback*" form also includes a button in which the subject ends the simulation.

Table 4-3 Feedback questionnaire

Number	The asked question	Field type	Available choices	Remarks
1	Did you find the traffic information provided in this simulation useful?	Combo box	1- Yes 2- No	
2	Do you prefer receiving this information?	Combo box	1- Yes 2- No	
3	How do you like to receive this information before the trip?	Combo box	1- Radio 2- TV Reports 3- Internet 4- Other	Enabled only if question #2's answer is Yes
4	How do you like to receive this information while the trip?	Combo box	1- Radio 2- Special system 3- Other	Enabled only if question #2's answer is Yes
5	Do you agree to install this device into your vehicle?	Combo box	1- Yes 2- No	
6	How much would you like to pay for installing this device into your vehicle?	Combo box	1- \$100-200 2- \$200-300 3- \$300-400 4- \$400-600 5- \$600-800 6- \$800-1000 7- \$1000-1200 8- \$1200-\$1500 9- > \$1500	Enabled only if question #5's answer is Yes

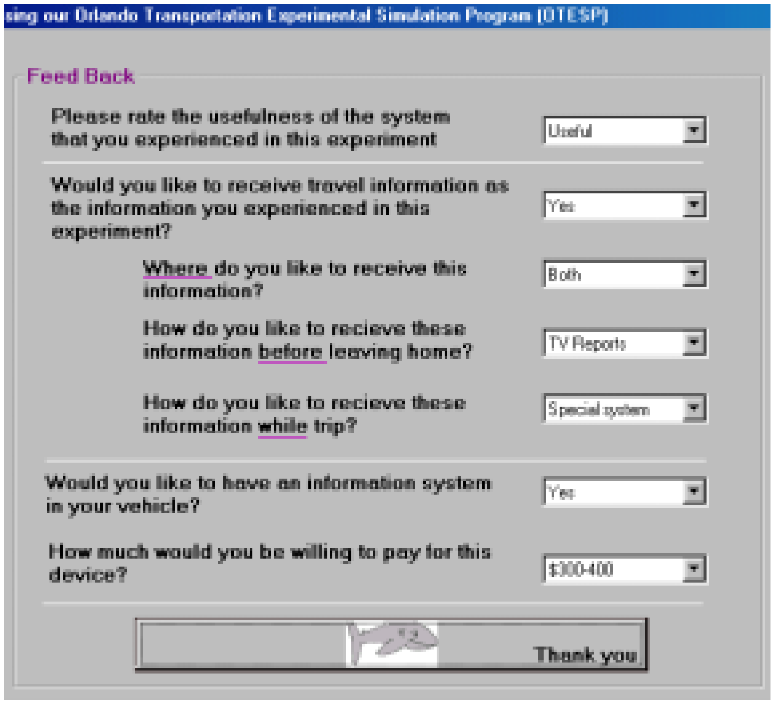

Figure 4-15 "*Feedback*" Form

CHAPTER 5

DATABASE DESCRIPTION

5.1 General Contents

OTESP creates one database file in which all information will be coded and written. This database file has four tables. The first table, named "*Personal Information*", is designed to capture the personal information of each driver in addition to his/her coded answers for the questions given to him in the "Personal Information" form. The second table, named "Normal Route", is designed to have the normal route for each subject. The third table, named "Simulation", captures all coded information coming from all simulated days. The final table, named "Feedback", saves subjects' answers for feedback questions.

5.2 "Personal Information" Table

This table has 27 fields. The first three fields have integer values for coding the driver's ID, day number, and movement number. The remaining 24 fields are designed to have the coded answers for the personal information questions according to the object type, see Table 4-2 and the following rule:

1. For combo boxes, the coded integer value will be:
    a. (–1) if the subject left this object without choice
    b. (0) for the first choice
    c. (1) for the second, and so on.
2. For check boxes, the coded integer value will be:
    a. (0) for uncheck box
    b. (1) for checked box

3. For option boxes, the coded integer value will be:
    a. (0) if the first option box is chosen
    b. (1) if the second option box is chosen
    c. (2) if the third option box is chosen, and so on.

5.3 "Normal Route" Table

This table has 43 fields. Again, the first three fields have integer values for coding the driver's ID, day number, and movement number as above. The remaining 40 fields represent the 40 links of the simulation. Each field has a binary value (0,1). "0" if the link is not in the normal route and "1" if it is. This table has only one record for each subject.

5.4 "Simulation" Table

This table has 92 fields with same first three fields as the above two tables. The remaining 89 fields are:

1. "*Bus-route-#1-travel-time*" field. It has the expected total travel time for bus route #1.
2. "*Bus-route-#2-travel-time*" field. It has the expected total travel time for bus route #2.
3. "*Bus-option*" field. Equal to 0 for drive option and 1 for transit option.
4. "*Chosen-route*" field. Equal to 1 if the user chooses bus route #1 and 2 if bus route #2.
5. "*Min-travel-time*" field. It has the expected minimum total travel time in case of driving.
6. "*Link1*" to "*Link 40*" fields. Have the current travel time for each link.
7. "*Alink1*" to "*Alink40*" fields. Have 1's if the link is in the shortest path and 0's otherwise.

8. "*Total-cost-so-fare*" field. It records the total toll cost in dollars from the beginning of each day until the current position of the simulated car.

9. "*Total-time-so-fare*" field. It records the total travel time in minutes from the beginning of each day until the current position of the simulated car.

10. "*Crash-link*" field. It records the link number that has the crash.

11. "*Chosen-direction*" field. It records the direction that the subject chooses. It has a unique value from the set {1,2,3,4} representing the four directions {north, south, east, west} Respectively.

12. "*Chosen-link*" field. It has the link code number that has been chosen for each movement.

5.5 "Feedback" Table

This table has 10 fields. The first three are similar to other tables and have the subject's ID, day number, and movement number. The remaining 7 fields are designed to have the coded answers to the given feedback question. All feedback questions are presented in the form of combo boxes. So, the coded values will be (–1, 0, 1, 2…) as above (see Table 4-3 and Section 5.2 for more details).

CHAPTER 6

INITIAL RESULTS OF THE PILOT STUDY

6.1 Introduction

A pilot study was conducted by running 10 subjects through the OTESP. The subjects were recruited from the University of Central Florida (UCF) where they work/study. The main goals of this pilot study are to:

- Check the capabilities of the simulation to be run by the subjects smoothly, friendly, and without any problems or confusion.
- Check the simulation output database file and its four tables where the coded values of all the subjects' characteristics and decisions as well as the coded traffic information values.
- Analyze the output (general descriptive statistics and the modeling process).

All the 10 subjects of this pilot study have successfully gone through the simulation until the end. Each subject went through 15 trial days from the network's origin (assumed subject's home) to its destination at UCF. The first 5 trial days for each subject, as he/she has been told before starting the simulation, are considered as training and the output has neither been saved nor analyzed. Each subject went through 10 simulated days in 5 different scenarios. Hundred routes have been chosen in this pilot study. Ninty-one of which were in the drive mode while 9 were in the transit (bus) mode. There are 879 movements that have been chosen through the 40 links of the simulation. Driving subjects have made 798 movements (963.43 miles) out of the 879 movements in the 5 different scenarios. While, transit subjects have chosen 81 movements (94.17 miles) in 9 trial days.

6.2 Characteristics of the Sample

As mentioned in chapter 2, Subjects are presented with "*Personal Information*" screen (see section 4.2.3) in which they are asked to answer some personal questions in the form of pull-down menus, combo boxes, text boxes, and option boxes (radio buttons). This questionnaire's goal is to collect general personal information as well as specific information about subjects' use of traffic information in both pre-trip and en-route modes. This section summarizes and analyzes this questionnaire. Tabulations, cross-tabulations using an analysis of frequency tables, and histogram charts are the method of analysis. The first table in OTESP's database file has the coded answers to this questionnaire.

6.2.1 Subjects' Personal Characteristics

This section summarizes the personal characteristics of the subjects of this pilot study. However, this pilot study includes only 10 subjects to check the simulation as well as to introduce the preliminary results of the analysis. The subjects' characteristics are summarized as follows (Figure 6-1 shows the graphical presentation of some of these results in more details):

- 90 % of the subjects (9 subjects) are in the middle age group (20-34)
- 90% of the subjects are males
- 60% are graduate students, 20% are faculty, and 10% are staff.
- 60% are in the low income group (< $15,000)
- 90% have driver license
- 70% own a car
- 60% drive alone while 40% share ride
- 70 % have used the bus before
- 30% have used the bus last month
- 20% have EPASS system installed in their vehicles
- 90% use the expressway system but 50% use it rarely.

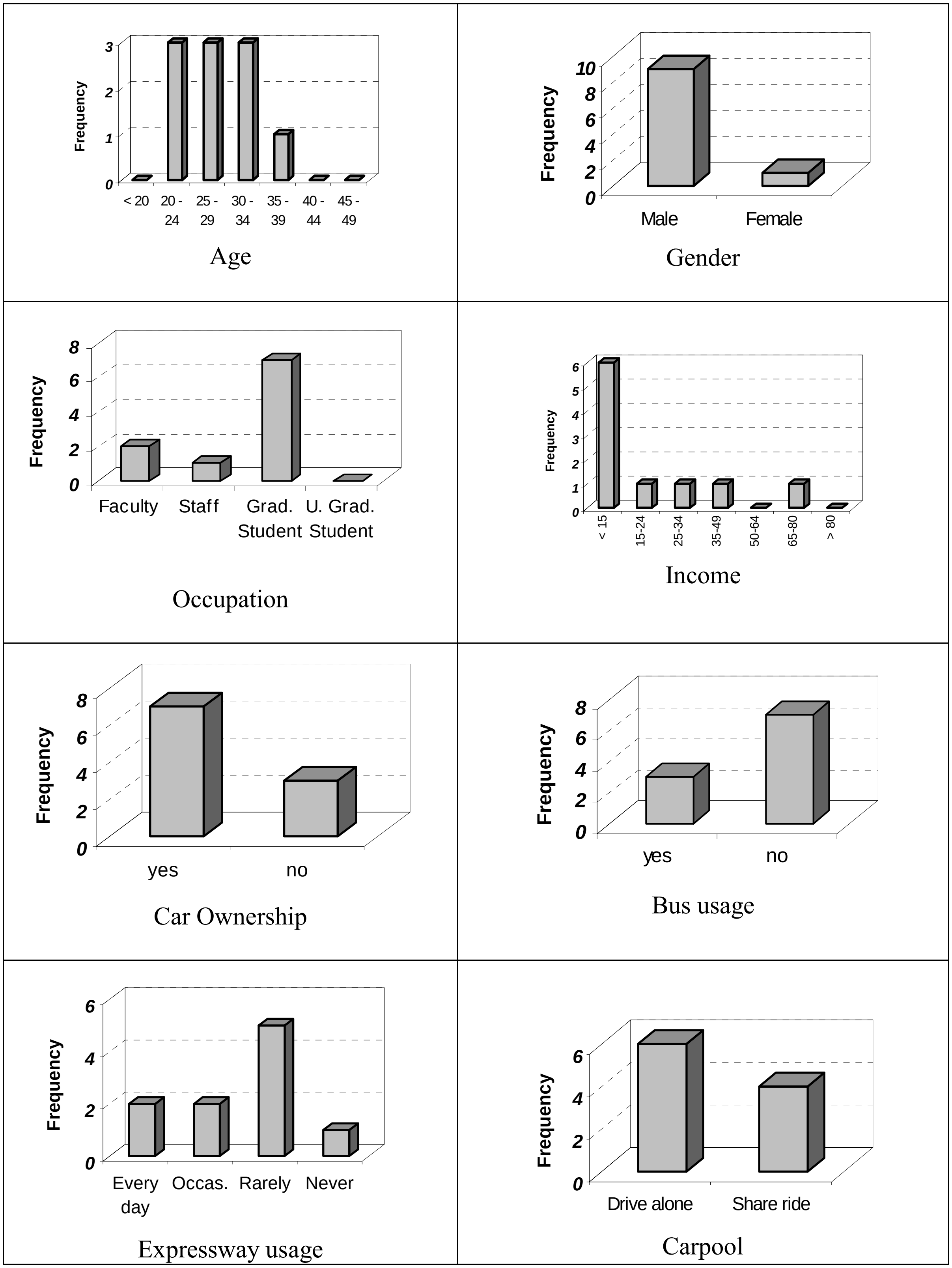

Figure 6-1 Subjects characteristics

6.2.2 Subjects' Familiarity with Traffic Information

This section provides a summary of the questionnaire that dealt with the familiarity of the subjects with both pre-trip and en-route traffic information. However, the results indicated that only one subject out of 10 has received traffic information using a TV report before making his trip. Sixty percent of the subjects have never received en-route traffic information while 40% have received it (see Figure 6-2).

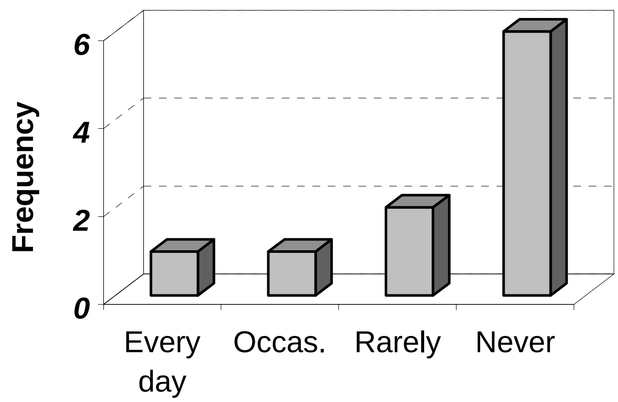

Figure 6-2 Frequency of receiving pre-trip traffic information

6.3 Mode/Route Choice Analysis

6.3.1 General Descriptive Analysis

The next step in the analysis was to identify and categorize the individual routes that were used by the subjects during the experimental trials. Routes were identified by the sequence of links that were traversed on a given trial day. As mentioned before, the study network consists of 40 links. The link numbers are used to identify frequency and relative frequency of individual route use. Table 6-1 and Figure 6-3 show the chosen routes in the first 5 trial days and Table 6-2 and Figure 6-4 show the chosen routes in the last 5 trial days. The analysis found that there were 15 distinct routes used more than once during the experimental trial days and that another 14 distinct routes were used only once during the trials. The bus route #1 has been used 4 times while bus route #2 has been used 5 times. Table 6-3 shows the routes' frequencies and descriptions. Route #16 is an aggregation of all routes chosen only once. Routes #17 and #18 are the bus route#1 and bus route #2 respectively. The first 15 routes represent 84.62% (77/91) of the chosen routes in the drive mode. The first most repeated two routes (route #1 and route #2) represent the two available expressway routes in this network, however, this is not surprising since the analysis is limited to the morning peak for commute drivers who try to minimize their travel times while they are going to work.

Table 6-4 presents the frequency of the minimum path routes calculated by the simulation (see section 4.2.5.5), however these minimum routes are available to the subjects as the pre-trip advice during scenarios 3 and 5 only (i.e., 4 trials out of 10 trials for each subject) while this advice disappears in scenarios 1, 2, and 3, it is still calculated in the background of the simulation and saved to the database file after the coding process. There appear to be some correlation between the route choice frequencies in Table 6-3 and the minimum route frequencies in Table 6-4. This correlation has two main reasons: first, the subjects are commuters and are familiar with the routes that have less travel time in normal situations unless there is a non-recurring congestion. Second, which might be more significant than the first reason, subjects are presented with these minimum routes in 40% of the days (2 scenarios out of 5) but limited to the drive mode only. However, in the 41.76% (38/91) of the drive mode trials, subjects of this pilot study have been provided with the minimum route as an advice.

Table 6-1 Routes' frequent choices in the first 5 trail days

Route #	Day1	Day 2	Day 3	Day 4	Day 5	Total
1	1	2	1	0	1	5
2	1	1	1	4	0	7
3	2	2	0	2	0	6
4	1	1	1	1	0	4
5	0	0	0	0	1	1
6	0	1	1	0	1	3
7	0	0	0	1	1	2
8	2	0	0	0	0	2
9	0	0	0	0	2	2
10	0	0	1	0	0	1
11	0	0	1	0	0	1
12	0	1	0	0	0	1
13	0	0	1	0	0	1
14	1	0	0	0	1	2
15	0	0	0	0	1	1
16	1	1	1	1	2	6
17	0	1	1	1	0	3
18	1	0	1	0	0	2
Total	10	10	10	10	10	50

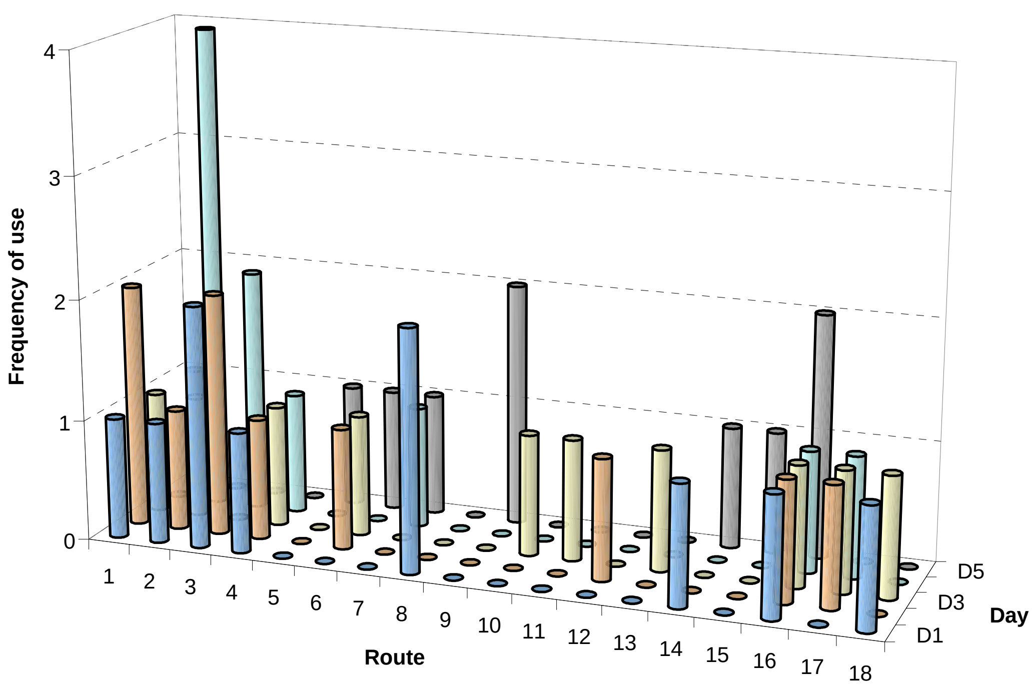

Figure 6-3 Routes' frequent choice at the first 5 trail days

Table 6-2 Routes' frequent choices in the last 5 trail days

Route #	Day1	Day 2	Day 3	Day 4	Day 5	Total
1	1	1	2	1	3	8
2	3	3	2	1	2	11
3	1	1	0	1	0	3
4	1	0	1	1	2	5
5	0	0	2	0	1	3
6	0	0	0	0	0	0
7	1	0	0	0	0	1
8	0	0	0	1	0	1
9	0	0	0	0	1	1
10	0	0	1	0	0	1
11	0	1	0	0	0	1
12	0	0	0	0	1	1
13	1	0	0	0	0	1
14	0	0	0	0	0	0
15	0	0	1	0	0	1
16	2	1	1	4	0	8
17	0	1	0	0	0	1
18	0	2	0	1	0	3
Total	10	10	10	10	10	50

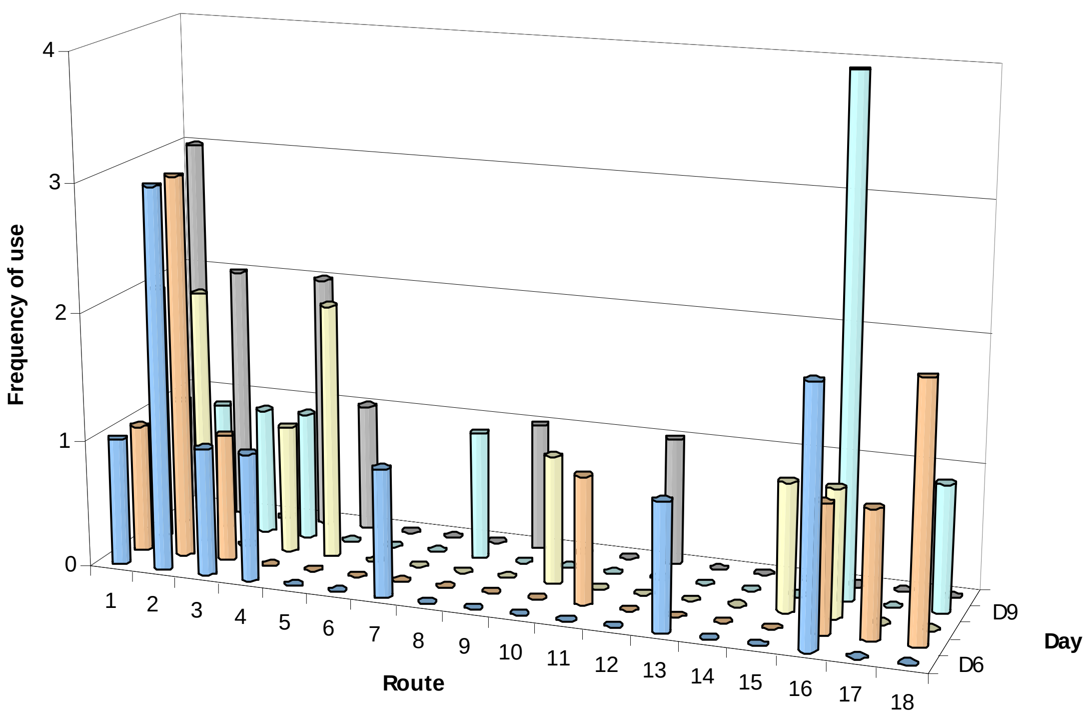

Figure 6-4 Routes' frequent choice at the last 5 trail days

Table 6-3 Chosen routes frequencies

Route #	Route links	Description	Frequency	Relative frequency
1	1, 23, 6, 29, 35, 19, 20, 21, 39	E-W Express (408), Greeneway (417), University Blvd.	16	16%
2	22, 5, 6, 7, 8, 9, 10, 40	E-W Express (408)	15	15%
3	22, 27, 33, 17, 18, 19, 20, 21, 39	Semoran (436), University Blvd.	9	9%
4	22, 27, 11, 34, 18, 19, 20, 21, 39	Semoran (436), Colonial Dr. (SR 50), University Blvd.	9	9%
5	22, 5, 6, 7, 8, 31, 37, 21, 39	E-W Express (408), Rouse Road, University Blvd.	4	4%
6	22, 27, 11, 12, 35, 19, 20, 21, 39	Semoran (436), Colonial Dr. (SR 50), University Blvd.	3	3%
7	1, 23, 28, 12, 35, 19, 20, 21, 39	Lake Underhill Dr, Goldenrod. (551), Colonial Dr. (SR 50), Greeneway (417), University Blvd.	3	3%
8	1, 2, 3, 4, 26, 32, 38, 39	Lake Underhill Dr, S. Alfaya Trl. (434)	3	3%
9	22, 27, 11, 12, 13, 14, 37, 21, 39	Semoran (436), Colonial Dr. (SR 50), Rouse Road, University Blvd.	3	3%
10	1, 2, 24, 30, 36, 20, 21, 39	Lake Underhill Dr, N. Dean Road (425), University Blvd.	2	2%
11	22, 5, 6, 29, 13, 14, 15, 38, 39	E-W Express (408), Greeneway (417), Colonial Dr. (SR 50), S. Alfaya Trl. (434)	2	2%
12	22, 5, 28, 34, 18, 19, 20, 21, 39	E-W Express (408), Goldenrod. (551), University Blvd.	2	2%
13	1, 2, 3, 25, 31, 15, 38, 39	Lake Underhill Dr, Rouse Road, Colonial Dr. (SR 50), S. Alfaya Trl. (434)	2	2%
14	22, 5, 6, 7, 8, 9, 32, 38, 39	E-W Express (408), S. Alfaya Trl. (434)	2	2%
15	22, 5, 6, 29, 13, 14, 37, 21, 39	E-W Express (408), Greeneway (417), Colonial Dr. (SR 50), Rouse Road, University Blvd.	2	2%
16	N/A	N/A	14 * 1	14 * 1%
17	Bus route # 1	Semoran (436), University Blvd.	4	4%
18	Bus route # 2	Semoran (436), Colonial Dr. (SR 50), S. Alfaya Trl. (434)	5	5%
		Total	100	100%

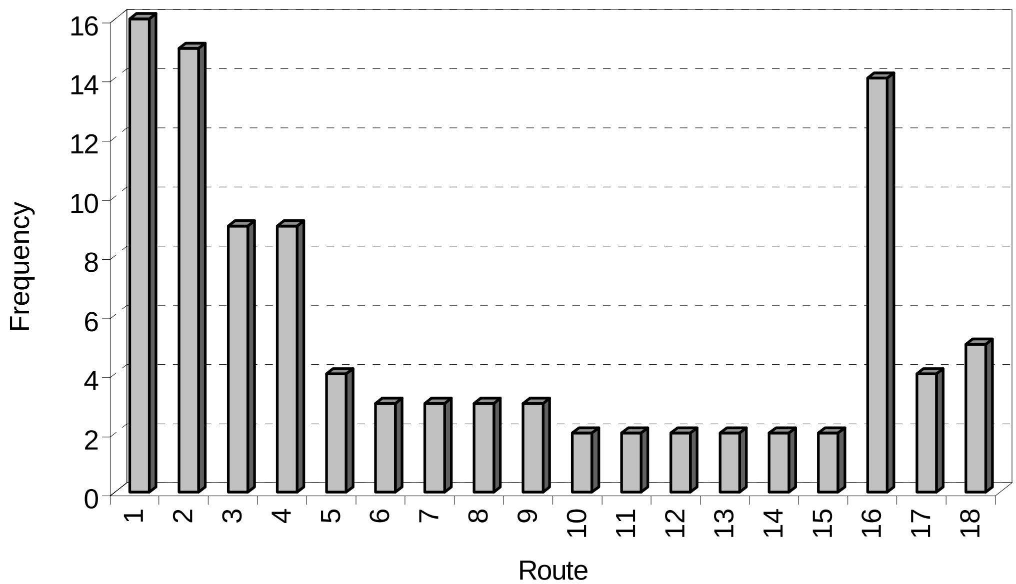

Figure 6-5 Chosen routes frequencies

Table 6-4 Minimum routes frequencies

Route #	Route links	Description	Frequency	Relative frequency
1	1, 23, 6, 29, 35, 19, 20, 21, 39	E-W Express (408), Greeneway (417), University Blvd.	51	56.04%
5	22, 5, 6, 7, 8, 31, 37, 21, 39	E-W Express (408), Rouse Road, University Blvd.	17	18.68%
6	22, 27, 11, 12, 35, 19, 20, 21, 39	Semoran (436), Colonial Dr. (SR 50), University Blvd.	10	10.99%
14	22, 5, 6, 7, 8, 9, 32, 38, 39	E-W Express (408), S. Alfaya Trl. (434)	2	2.20%
15	22, 5, 6, 29, 13, 14, 37, 21, 39	E-W Express (408), Greeneway (417), Colonial Dr. (SR 50), Rouse Road, University Blvd.	2	2.20%
11	22, 5, 6, 29, 13, 14, 15, 38, 39	E-W Express (408), Greeneway (417), Colonial Dr. (SR 50), S. Alfaya Trl. (434)	1	1.10%
16	N/A (not standard route)	N/A	8	8.79%
		Total	91	100.00%

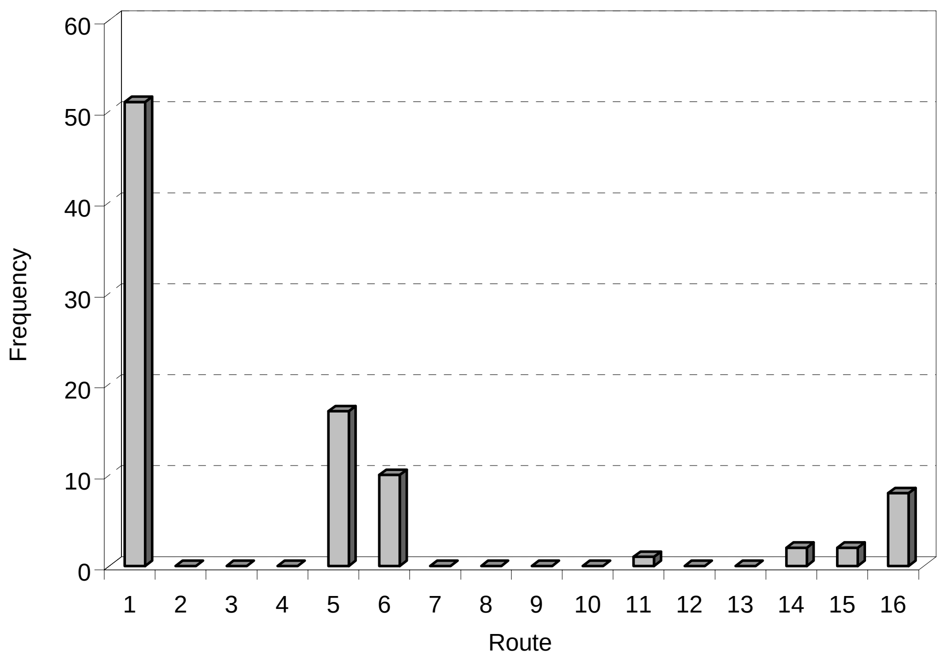

Figure 6-6 Minimum routes frequencies

To have a better understanding of the drivers' compliance with the information advice, Figure 6-7 presents a comparison between the number of subjects that followed the advised route in both scenarios 3 and 5 versus those who did not follow the advised route. About 33.33% (6 out of 18) of the drivers' choices followed the advised route without any diversion until the destination under scenario 3 conditions. Only 25% (5 out of 20) of the drivers followed the advised route without any diversion until the destination for scenario 5 conditions. The percent of drivers that followed the pre-trip advised route decreased from scenario 3 to scenario 5 to prove that the updated en-route traffic information/advice given in scenario 5 had an effect on the subjects. It seems that 8.33% of the subjects' choices (the difference between the 33.33% and the 25%), followed the disseminated en-route advised route that updates while a subject moves on the network. Hence, we can conclude that at least 33.33% of the subjects follow the advice. While, about 66.66% of the subjects have high inertia to change their normal routes. Table 6-5 has more details.

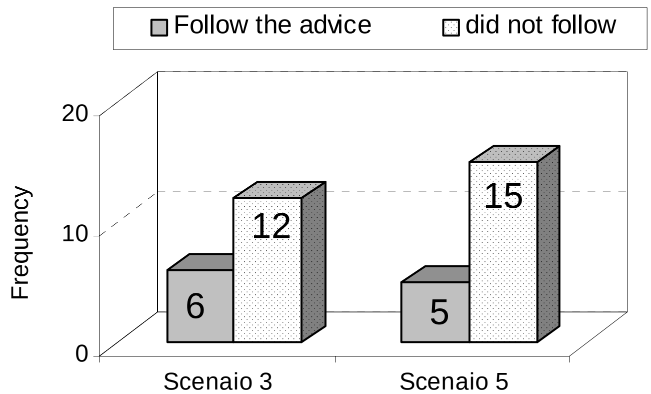

Figure 6-7 Driver compliance to the advised route

Table 6-5 Numbers of drivers followed the advised route

Scenario	Day	Bus usage	Drive	# Drivers following the advised route, excluding the bus trials
1	1	1	9	0
	6	0	10	0
2	2	1	9	1
	7	3	7	0
3	3	2	8	3
	8	0	10	3
4	4	1	9	1
	9	1	9	0
5	5	0	10	2
	10	0	10	3

6.3.2 Previous Traffic Information Effect

From the OTESP's 5 scenarios of traffic information with and without advice disseminated to the subjects for both mode and route choosing, Scenario 1 has no traffic information provided to the subjects. In the normal route form (see section 4.2.4), each subject is asked to enter into the simulation his/her preferred route (normal route) from the origin to the destination in a normal morning trip. Day 1 is the beginning of the actual simulated days. Day 6 is a trial that before it a subject went through and seen all the different scenarios of the simulation. The goal of this section is to study the subjects' inertia of diverting from their normal routes in the case of no information available. From

Table 6-6, 75% (6 out of 8) of the subjects have chosen their normal routes in day 1 (after excluding route 16 and the bus routes). On the other hand, 50% (4 out of 8) of the subjects have chosen their normal routes in day 6 (after excluding route 16 and the bus routes). Then, it can be simply concluded that the previous traffic information (information of the last days) have an effect on the subjects. In other words, the previous days' information cause 25% of the subjects to divert from their normal routes in day 6 (where there is no information provided).

6.3.3 ANOVA between the Travel Time and the Subject Characteristics

Analysis of variance (ANOVA) performs comparisons like the t-test, but for an arbitrary number of factors. Each factor can have an arbitrary number of levels. In this analysis, ANOVA between the chosen-route travel time and the characteristics of the subject (as dummy variables) have been conducted. Interaction terms are also included. Table 6-7 shows the ANOVA results. The results show that there is a significant increase in the travel time for the routes chosen by student subjects versus the faculty/staff subjects, indicating a possible effect of income and value of travel time. Also, there is a significant decrease in the travel time for those subjects who use the expressway system every day or usually versus those who use it rarely or never. Income is also significant.

Table 6-6 Subjects' inertia of diverting from their normal routes

Subject	Normal route	Day 1	Day 6
1	3	3	3
2	2	2	2
3	1	1	7
4	8	8	2
5	16	16	1
6	2	8	2
7	3	3	16
8	4	4	4
9	16	Bus Route #2	13
10	8	14	16

Table 6-7 ANOVA results between the chosen-route travel time and the subject characteristics

Dummy Variable	Level 0	Level 1	Mean		F-stat	P-value
Age, 1 if > 30 yrs	60	40	26.4	26.6	0.01	0.917
Gender, 1 if female	90	10	26.8	23.4	1.47	0.228
Student, 1 if student	30	70	23.8	27.6	4.09	0.046
Income, 1 if > $15,000	60	40	27.8	24.5	3.73	0.056
D-license, 1 if has D.L.	10	90	24.3	26.7	0.72	0.397
Dl-Long, 1 if has it for > 5 yrs	60	40	26.8	25.9	0.27	0.606
EPASS, 1 if he has EPASS system	80	20	26.7	25.4	0.37	0.547
Bus usage, 1 if > 10 times last month	30	70	27.2	26.2	0.29	0.59
Expressway usage, 1 if every day or usually	50	50	28.71	24.26	7.04	0.009
Frequency of receiving pre-trip traffic information, 1 if every day or usual	80	20	27.0	24.4	1.43	0.234
Frequency of receiving en-route traffic information, 1 if every day or usual	70	30	27.2	24.6	1.97	0.164
Information disseminated, 1 in case of scenario 2,3,4, or 5	26	74	28.2	25.8	1.4	0.239
Interaction terms						
1 if student has D.L. for a period > 5 yrs	80	20	26.2	27.8	0.54	0.464
1 if student use the expressway every day or usually	90	10	26.6	25.5	0.16	0.694
1 if student receive pre-trip traffic information every day or usually	90	10	26.7	24.5	0.55	0.462
1 if student receive en-route traffic information every day or usually	90	10	26.5	26.3	0.002	0.946
1 if an old subject (>30 yrs) under scenario 2,3,4, or 5	77	23	26.8	25.2	0.69	0.409
1 if female subject under scenario 2,3,4, or 5	91	9	26.8	23.4	1.31	0.256
1 if a subject has EPASS under scenario 2,3,4, or 5	86	14	26.6	25.8	0.1	0.752

6.3.4 En-route Short-Term Choice Analysis

The simulation provides link-choice capability when approaching every node while drivers move on the network. The goal of this section is to have a better understanding of how well a commute driver's short-term-choice would be if he/she is provided with the true travel times and the congestion levels of the coming links. OTESP's database file has the coded travel times and the congestion levels. During the 5 different scenarios, the 10 subjects of this pilot study made 798 movements (decisions) while moving on the 40 links of the OTESP's network in the drive mode. Before each movement, the simulation updates the network travel times of all the links and assigns 3 different colors to represent the level of congestion (green, yellow, and red). This information is available to the subjects in scenarios 2 and 3 as only pre-trip traffic information and in scenarios 4 and 5 as en-route traffic information. However, the simulation codes and writes this information for all the 5 scenarios to the database file.

At each node, the subject is required to make a decision and choose between the two coming links. This choice is considered positive if the driver has chosen the link that had less level of congestion (green while the other was yellow or red, or yellow while the other was red). On the other hand, the choice is considered negative if the driver has chosen the link that had high level of congestion (red while the other was green or yellow, or yellow while the other was green). There are 555, out of the 798 movements, that have been excluded from the short-term-route choice analysis because each decision has been done under one of the following two special cases:

1. The driver had no choice but continue to the destination. For example, the University Blvd. nodes (see Figure 4-1). This happens if a driver is located at one of the following nodes: (5, 12, 18, 19, 20, 21, 22, 23, or 24)
2. The two coming links were at the same level of congestion. For example, both links are green)

After excluding these 555 movements, out of the remaining 243, 135 decisions are found to be positive while 108 decisions are found to be negative. Figure 6-8 shows a graphical presentation for these short-term choices distributed between the 10 trial days.

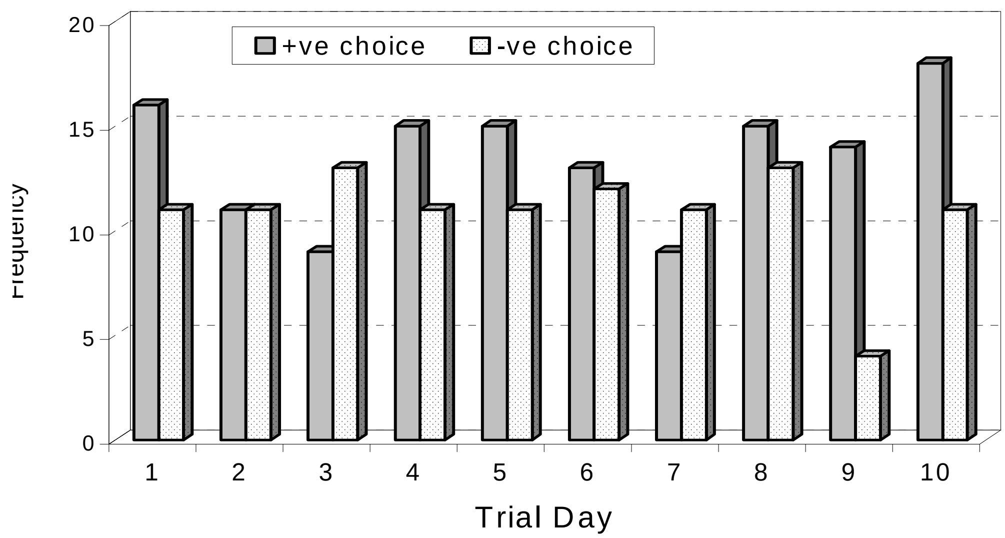

Figure 6-8 Short-term choices

From Figure 6-8, it can be seen that the frequency of positive-short-term choices are higher for days 4, 5, 9, and 10 (scenarios 4 and 5) where the en-route traffic information are disseminated to the drivers. Hence, drivers have used this information to enhance their choices and minimize their travel time (modeling results are discussed hereafter). On the other hand, there is no clear relationship between the frequencies of the positive-short-term and negative-short-term choices for days 2, 3, 6, and 7 (scenarios 2 and 3) where there were no en-route information disseminated to the drivers. There is a slight increase in the positive-short-term choices for days 1 and 6 (scenario 1), this could be the case because drivers had no information and they used their normal routes which are already biased toward the expressways which experience less congestion and have small variances over the free flow travel times.

6.3.5 Applying Nested Logit Model to Predict Mode/Route Choice

In this pilot study, 100 routes have been chosen between the origin and the destination. Eighty routes were chosen in the presence of one of the traffic information scenarios disseminated to the drivers during the simulation. While, 20 routes were selected without information provided to the subjects. These 100 routes are classified into 3 main choices as follows: taking the bus (aggregation of bus route #1 and bus route #2), driving on the expressway system (aggregation of routes #1 and route #2), and driving on routes other than the expressway system (aggregation of routes #3 through #16). In other words, D1 is the aggregation of routes 1 and 2 and D2 is the aggregation of the all other roads. These three choices formulate the structure of the nested logit model used in this study (see Figure 6-9).

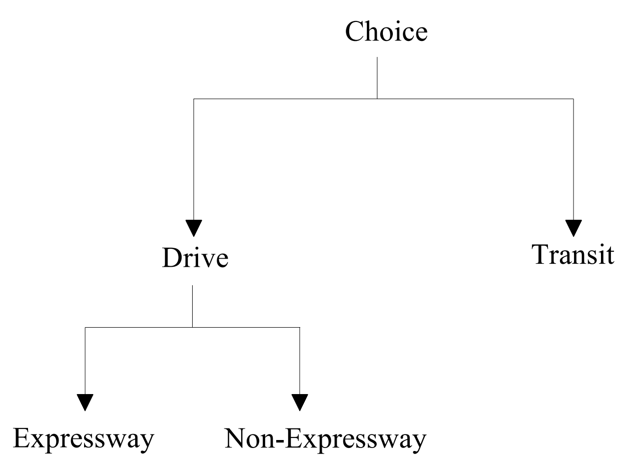

Figure 6-9 Nested logit model structure for mode/route choice model

The OTESP's database file has 22 different characteristics for each subject. However, some of these variables are found to be 100% linearly related. i.e., they have the same coded values saved to the database file. The direct reason for that is the low number of subjects in this pilot study.

Travel time of each alternative is considered one of the independent variables. Travel time of each alternative is chosen as the following:

travel time of the bus choice is the average travel time of the two bus routes

travel time for the second choice is the average travel time of route #1 and route #2.

travel time for the third choice is the average travel time of routes #3 through #16.

Three variables of the subjects' characteristics are included in the model. The overall model is found statistically significant based on the chi-square test. Table 6-8 presents the estimation results of this nested logit model. The inclusive value coefficient is significantly different from one. This provides a statistical validation of using the nested logit structure.

The travel time is significant in each alternative's equation. The subjects' characteristic variables are found to be statistically significant at least in one of the three equations. For example, subject's frequency of receiving en-route traffic information is significant (t-stat = 2.836) in the second equation (drive on non-expressway system). However, positive coefficient, as the frequency of receiving en-route traffic information increases the probability of choosing drive on non-expressway increases. This explanation can be used for the other two variables (high-income and subject's frequency of using the expressway system).

Table 6-8 Estimation of nested logit mode/route choice model

Variable	Coef.	t-stat	p-value
Travel time; Route specific variable	-0.126	-2.507	0.012
Subject specific constants			
Drive on Expressway			
Frequency of receiving en-route traffic information; 1 if receives information every day or usually	-0.556	-1.789	0.075
High income; 1 if income > $15,000	0.042	1.82	0.069
Frequency of using the expressway; 1 if uses the expressway every day or usually	0.884	2.065	0.039
Drive on routes other than the Expressway			
Frequency of receiving en-route traffic information; 1 if receives information every day or usually	1.232	2.836	0.005
High income; 1 if income > $15,000	-0.868	-2.158	0.044
Frequency of using the expressway; 1 if uses the expressway every day or usually	-0.228	-1.732	0.084
Inclusive value parameters			
Drive	4.546	2.028	0.043
Bus	3.519	2.367	0.018
Number of observations	100		
Log likelihood [LL($\boldsymbol{\beta}$)]	-63.768		
Res. Log likelihood [LL($\mathbf{0}$)]	-132.391		
Pseudo-R^2 = 1 - LL(0) / LL($\boldsymbol{\beta}$)	0.518		
Prop [chi squared > value]	< 0.001		

6.3.6 Applying Binomial Logit/Probit Models to Predict En-Route Short-Term Choice

The binomial logit/probit is an estimation technique for equations with dummy dependant variables that avoids the unboundedness problem of the linear probability model by using a variant of a cumulative logistic function for the logit models and by using a variant of the cumulative normal distribution for the probit models. Both models are used to test the effect of the drivers' characteristics on their short-term choices as well as the effect of the travel time of the chosen and not-chosen link. As each link has its own distance and hence free flow travel time different from others, then, the difference between the travel time and the free flow travel time is taken into consideration instead of the link travel time and called "Delay". DELAY1 is the difference between the travel time and the free flow travel time of the chosen link while DELAY2 is the difference between the travel time and the free flow travel time of the not-chosen link. The binary dependant variable in this model takes "1" if a driver made a good decision by choosing the link with minimum congestion (for example, green link while the other was red) and takes "0" for the bad decision. Table 6-9 and Table 6-10 represent the modeling results. The likelihood ratio statistic values (twice the difference between the log likelihood values of the unrestricted and restricted models) are 51.91 and 52.57 with 8 degree of freedom for the binomial logit and probit models, respectively. The likelihood ratio is distributed as χ^2 distributions. The critical value is 15.51 for 8 degrees of freedom at 5% level of significance. This means that the null hypothesis of all coefficients are jointly zero is rejected for the both models. Hence, both models are statistically significant with 5% significance level.

Both models share the significant variables. Six variables are found to be statistically significant based on their t-test results from the Table 6-9 and Table 6-10. The first two significant variables are DELAY1 and DELAY2 that addressed the statistical significance of the en-route short-term traffic information on the drivers' choices. The negative coefficient of DELAY1 indicates that as the difference between a link travel time and its free flow travel time increases, the probability of choosing this link goes down. And the same for DELAY2, its positive coefficient indicates that as the difference between a link travel time and its free flow travel time increases, the probability of not choosing this link goes up.

Gender is also a significant variable in this model. However, the probability of choosing a right decision is higher for females. The fourth significant variable is the dummy variable (COWNER) which has a value of 1 for a subject owning a car and 0 if he does not. The positive coefficient in this case indicates that the probability of making a right decision goes up for those subjects who own a car. The last two significant variables are EnrouteFreq and ExpressFreq that addressed the subjects' frequency of receiving en-route traffic information and using expressway system respectively. The positive coefficient of the first variable can be interpreted as that the probability of choosing the less congested link (right decision) goes up as the frequency of receiving en-route information goes up. The same interpretation applies to the EnroutFreq variable.

Table 6-9 Short-term binomial logit modeling results

Variable	Description	Coeff.	Std. Err	z-Stat	P-value
C	Constant term	-9.706	3.965	-2.448	0.014
GENDER	1 if Female subject, 0 if Male	7.798	3.687	2.115	0.034
INCOME	1 if income > $15,000, 0 otherwise	0.558	0.339	1.648	0.099
MOVEMENT	Number of movements have been done since the origin	0.252	0.196	1.285	0.199
ENROUTEFREQ	1 if subject receives en-route traffic information everyday or occasionally, 0 if rarely or never	2.381	1.029	2.313	0.021
EXPRESSFREQ	1 if subject uses the expressway everyday or occasionally, 0 if rarely or never	2.060	1.034	1.993	0.046
COWNER	1 if the subjects owns a car, 0 otherwise	3.317	1.496	2.217	0.027
DELAY1	Travel time of the chosen link – its free flow travel time	-1.473	0.531	-2.771	0.006
DELAY2	Travel time of the not-chosen link – its free flow travel time	1.869	0.515	3.628	0.000
Mean Y	0.626				
S.E. of regression	0.384				
SSR	13.287				
Log likelihood	-39.476				
Res. Log likelihood	-65.431				
LR statistic (8 df)	51.910				
Prob. (LR stat)	< 0.001				

Table 6-10 Short-term binomial probit modeling results

Variable	Description	Coeff.	Std. Err	z-Stat	P-value
C	Constant term	-5.721	2.296	-2.491	0.013
GENDER	1 if Female subject, 0 if Male	4.564	2.134	2.138	0.033
INCOME	1 if income > $15,000, 0 otherwise	0.326	0.192	1.700	0.089
MOVEMENT	Number of movements have been done since the origin	0.154	0.115	1.347	0.178
ENROUTEFREQ	1 if subject receives en-route traffic information everyday or occasionally, 0 if rarely or never	1.405	0.598	2.350	0.019
EXPRESSFREQ	1 if subject uses the expressway everyday or occasionally, 0 if rarely or never	1.203	0.591	2.035	0.042
COWNER	1 if the subjects owns a car, 0 otherwise	1.952	0.865	2.257	0.024
DELAY1	Travel time of the chosen link – its free flow travel time	-0.893	0.315	-2.838	0.005
DELAY2	Travel time of the not-chosen link – its free flow travel time	1.112	0.292	3.808	0.000
Mean Y	0.6263				
S.E. of regression	0.3838				
SSR	13.261				
Log likelihood	-39.144				
Res. Log likelihood	-65.431				
LR statistic (8 df)	52.573				
Prob. (LR stat)	< 0.001				

6.4 Feedback Questionnaire Analysis

After finishing the 10 simulated days, each subject is required to give an answer for 7 feedback questions, see Table 4-3 for the wording of these questions. Figure 6-10 shows the graphical representation of the subjects' answers to these questions. No subjects stated that this experimental simulation was not useful. Also, 100% of the subjects stated that they would like to receive at least one of the types of the information disseminated to them in this simulation.

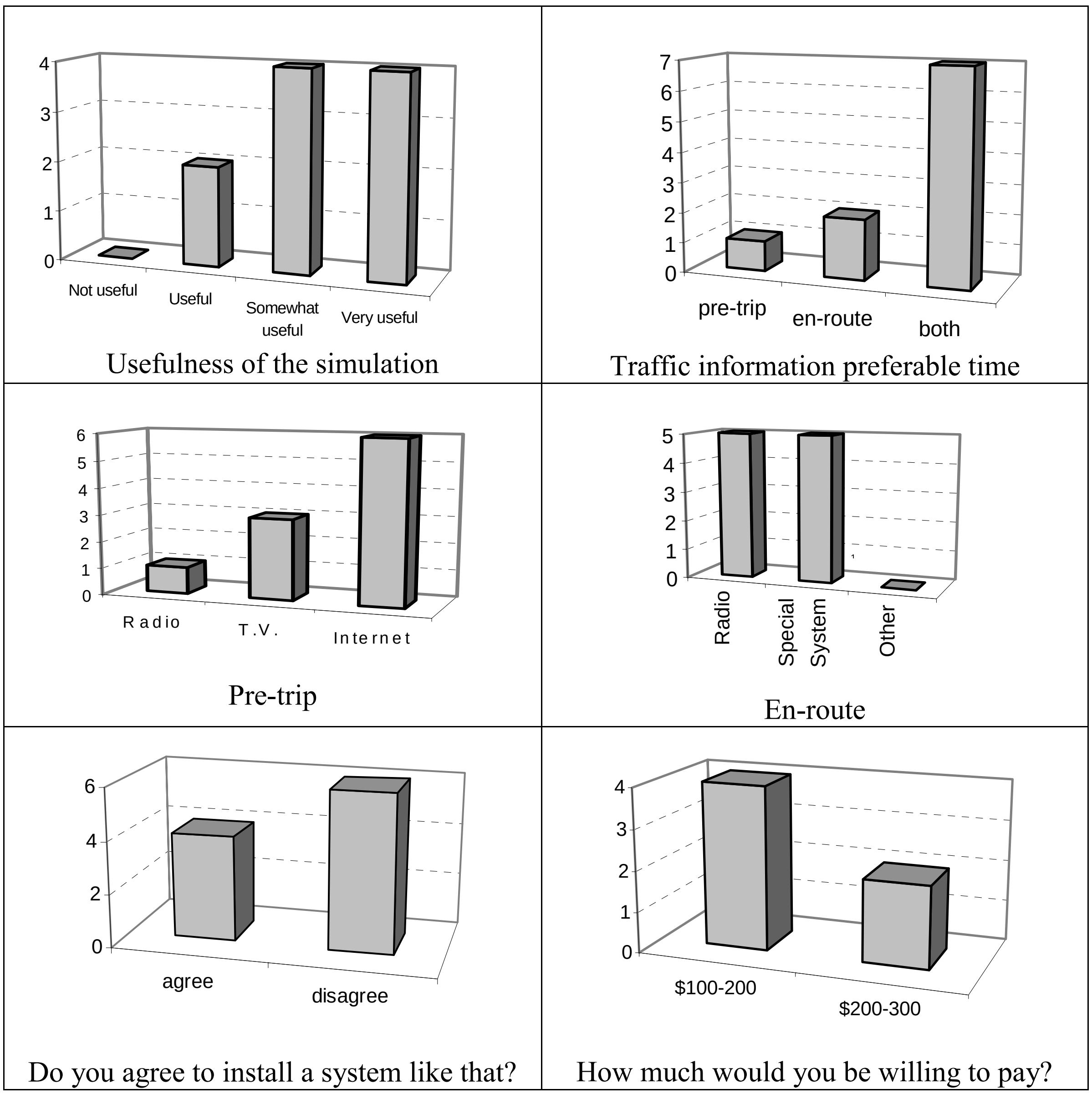

Figure 6-10 Feedback questionnaire results

CHAPTER 7

CONCLUSIONS

As data collecting tools for route choice modeling purposes under ATIS, researches have used mail-in surveys, telephone surveys and Internet surveys. However, in recent years, they have used computer simulation programs as data collection tools to have a better understanding of drivers' behavior under ATIS. To understand which of the factors; human, traffic information type, accuracy, and method of dissemination, that are most important in mode/route choice analysis is not a simple task. This study presents the design and development of an interactive computer simulation tool (named "OTESP" stand for Orlando Transportation Experimental Simulation Program) applied on a portion of the Orlando network captured from a GIS database. This study also presents the analysis of the initial results of the pilot study where 10 subjects have successfully went through the simulation until the end. This simulation is being used as a tool to collect route/mode choice data. This simulation is unique since it combines route and mode choices under ATIS in a real network environment.

A visual basic program has been developed to capture this roadway network and simulate a moving vehicle on the network. A subject has the ability to move a simulated vehicle on different segments of the network using the computer's mouse. Different levels of traffic information are provided to the subjects, including transit and route information, pre-trip and en-route information, and information with and without advice. The subject makes different travel choices while he/she travels on the network from a specified origin to a specified destination. Different travel congestion levels are also provided. All the travel decisions are captured and coded to a database for analyses. The data base file includes 4 tables that have 172 fields and an average of

100 records for each subject. The experiment starts and ends with a short survey to collect the subjects' socio-demographic characteristics, preferences, and perceptions. The initial study is conducted by running the OTESP simulation through 10 subjects randomly recruited from the (UCF) where they work/study. This initial study has achieved its goals in terms of checking the simulation capabilities. The OTESP was simple to all the 10 subjects to run. Also, the output database file of this study with its four tables (all of 172 fields) was checked and found to have the correct coded values for all the simulation variables.

Hundered routes have been chosen in this pilot study, 91 of them were in the drive mode while, 9 were in the transit (bus) mode. A total of 879 movements have been chosen through the 40 links of the simulation. Driving subjects have chosen 798 of which (963.43 miles) in the 5 different scenarios, while transit subjects have chosen 81 movements (94.17 miles) in 9 trial days. The analysis found that there were 15 distinct routes used more than once during the experimental trials and that another 14 distinct routes were used only once during the trials. The bus route #1 has been used 4 times while bus route #2 used 5 times. The results showed that 33.33% of the drivers followed the advised route without any diversion until the destination under pre-trip information with advice scenario. About 8.33% followed the updated en-route advised route link-by-link from the current position to the destination. Twenty five percent of the driving subjects have changed their normal route in trial day #6 where there is no information provided. This simply means that previous traffic information (information of the last days) have an effect on the subjects. In the feedback questionnaire, none of the subjects stated that this experimental simulation was not useful. Also, 100% of the subjects stated that they would like to receive at least one of the types of information disseminated to them in this simulation. Sixty percent prefers the Internet as a source of pre-trip traffic information, while 50% prefer the radio for the en-route traffic information while driving against the other 50% prefer a special system installed in their vehicles.

Two preliminary modeling efforts were presented in this study. The first modeling effort was based on a nested logit model. A nested logit model was used to analyze and understand the complex travelers' decisions in the mode/route choices. The dependant variable was the choice of one of the following three alternatives; take the bus, drive on the expressway system, and drive on routes other than the expressway system (the last two alternatives are put together in one nest). The travel time was considered as an independent variable in addition to three relevant subjects' characteristics. The travel time is significant in each alternative's equation. The subject's frequency of receiving en-route traffic information is significant (t-stat = 2.836) in the second equation (drive on non-expressway system). As the frequency of receiving en-route traffic information increases the probability of choosing drive on non-expressway increases.

The second modeling effort was based on applying binomial logit/probit models to predict en-route short-term choice (link choice) and to test the effect of the drivers' characteristics on their short-term choices as well as the effect of the travel time of the chosen and non-chosen links. The binary dependant variable takes a value of "1" if the driver made a good decision by choosing the link with minimum congestion. Delay time on each link and 11 subject's characteristics were the independent variables. Both models (logit and probit) are found significant with Log likelihood ratios of 51.91 and 52.57 respectively distributed as χ^2 distributions. Both models results showed that the delay of the both chosen and not-chosen links were significant. Also owing a car was found to be significant.

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