TRB Paper #04-2963

MODELING REPEATED MULTINOMIAL ROUTE CHOICES UNDER ADVANCED TRAVELER INFORMATION SYSTEM USING GENERALIZED ESTIMATING EQUATIONS WITH POLYTOMOUS LOGIT FUNCTION

Mohamed Abdel-Aty, Ph. D., P.E.
Department of Civil & Environmental Engineering
University of Central Florida
Orlando, FL 32816-2450
Phone: (407) 823-5657
Fax: (407) 823-3315
Email: mabdel@mail.ucf.edu

Fathy Abdalla, Ph.D. Candidate
Department of Civil & Environmental Engineering
University of Central Florida
Orlando, FL 32816-2450
Phone: (407) 823-4552
Fax: (407) 823-3315
Email: mabdalla@pegasus.cc.ucf.edu

Transportation Research Recor: Journal of the Transportaion Research Board, No. 1882, TRB, National Research Council, Washington, D.C., 2004. pp.61-69

MODELING REPEATED MULTINOMIAL ROUTE CHOICES UNDER ADVANCED TRAVELER INFORMATION SYSTEM USING GENERALIZED ESTIMATING EQUATIONS WITH POLYTOMOUS LOGIT FUNCTION

ABSTRACT
Correlated multinomial route choice data were modeled under an advanced traveler information system (ATIS). A travel simulator was used as a dynamic data collection tool. The simulator uses realistic network and real historical traffic volumes. It provides five levels of ATIS and accounts for types of delay. A 25-node and 40-link network was used. Sixty-three qualified subjects performed a total of 539 trial days. Forty-four distinct routes were chosen. The multinomial generalized estimating equation (MGEE) methodology was used with a generalized polytomous function and an exchangeable correlation structure. MGEEs account for the serial correlation between repeated choices made by the same subject as well as the correlation due to the overlapping between alternatives. The modeling results show that drivers can identify and follow the shortest path when they are provided with advice-free traffic information on all the network links. In addition, it is shown that the odds of choosing a certain shortest-path route, whether the drivers are advised or not, vary from route to route, depending on the characteristics of the route itself. It was proved that the proposed model could account for a correlation in the multinomial repeated route choices with simple computational effort, even for a large number of alternatives.

Keywords: ATIS, multinomial route choice, repeated observations, routes' overlap, MGEE

INTRODUCTION

The implementation of ATIS technologies in real life is limited and still in its starting phases. Over the last decade, transportation research that would lead to a better understanding for the effect of ATIS on multidimensional route choice models in realistic complex networks was limited. The limitation was due to the computational effort needed. Especially when a relatively large network with overlapping links between routes is used and each participant made more than one observation (choice). In this paper, the Orlando Transportation Experimental Simulation Program (OTESP) was used to collect multidimensional route choice data. OTESP is an interactive windows-based computer simulation tool. It simulates commute home-to-work morning trips. A Portion of the city of Orlando network was captured from a GIS database (Figure 1). The network consists of 25 nodes and 40 links. This network has been carefully chosen from the Orlando network. It comprises different types of highways. It includes 6-lane principle arterials, 4-lane principle arterial, 6-lane minor arterial, 2-lane minor arterial and local collectors. The network also includes two expressways.

The subject is presented with a real map for the network and has the ability to move his/her vehicle on the network from intersection to another. OTESP's code is fed with real historical traffic volumes on all network links. Based on these volumes, the geometric characteristics of the network roadways, and the HCM standards, the simulator generates a random speed for every link on the network. This generated speed accounts for delays caused by intersections, recurring congestion, non-recurring congestion (incident), queuing at toll plazas, and weather condition effects. All links' speeds are updated every time the subjects approach an intersection. The speed of a link, at a certain movement, controls the speed of the simulated vehicle so that the subject feels the delay. OTESP was distinctively designed to give the subject the feel of a realistic situation. Therefore, the simulator does not interfere with the accuracy of the information, whatever speed is generated for a particular movement (whether the travel time is provided to the subject or not) is assumed accurate for the current movement. The simulator provides the travel time value on every link as quantitative information while every link on the map takes a color representing its traffic congestion (green, yellow, or red for free, moderate, or congested flow). Therefore, the information given is both descriptive and prescriptive. Figure 1 shows an example of the OTESP's user-interface and network.

At every trial day, OTESP provides one of five different scenarios (levels) of information/advice to the subject including: no information (scenario #1), pre-trip information without and with advice (scenarios #2 and #3, respectively), and en-route information (in addition to the pre-trip information) without and with advice (scenarios #4 and #5, respectively). During the actual experiment, OTESP presents ten simulated days (two days for each scenario). There is no difference in the travel time computations across the scenarios. The differences between the five scenarios are only in the level of the information/advice provided to subjects and whether they are pre-trip or en-route. OTESP also provides three different weather conditions (clear sky, light rain, and heavy rain). The Moore's shortest path algorithm (1) has been employed in the code of OTESP to determine the travel-time-based shortest path from any node to the destination, which is introduced as advice to the subjects in some scenarios. The simulator starts and ends with a short survey to collect the subjects' socio-demographic characteristics, preferences, perceptions, and feedback. A four-table database is created to capture all the information/advice provided and the traveler decisions. For detailed design and description of the simulator and the network, the reader is referred to Abdel-Aty and Abdalla (2,3). Abdel-Aty and Abdalla (3) illustrated the validity of the data and the simulator as a route-choice data collection tool.

Two different kinds of correlation arose in this study because each subject made multiple route choices and because the chosen routes sometimes have overlapping links. These correlations must be taken into account. Otherwise the results will be biased (4,5). In this paper, a Multinomial Generalized Estimating Equations (MGEEs) methodology was used with generalized polytomous function and exchangeable correlation structure to account for the correlation.

BACKGROUND

A considerable number of studies have examined the potential benefits of providing pre-trip and en-route real-time information to travelers. Polydoropoulou et al. (6) and Khattak et al. (7) concluded that drivers exhibit some inertia for using their normal route, especially for home-to-work trips. Polydoropoulou found that drivers are more likely to divert to another route when they first learn of a delay before the trip. Drivers are less likely to divert during bad weather, as alternative routes might be equally slow. Abdel-Aty et al. (8) showed that traffic information should be provided with alternative route information as well.

Khattak et al. (7) found that travelers who are unfamiliar with alternative routes or modes are particularly unwilling to divert. This conforms to the study of Kim and Vandebona (9), which concluded that drivers who are familiar with alternative routes have a high propensity to divert from their normal routes. Accurate quantitative information might enable drivers to overcome their behavioral inertia. Further, the commuters were generally willing to comply with advice from a prescriptive ATIS (7,10). Adler and McNally (11) proved that travelers who are more familiar with the network are less likely to consult information. Bonsall et al. (12) found that user acceptance declined with decreasing quality of advice in an unfamiliar network. As familiarity with the network increased, drivers were less likely to accept advice from the system. However, Allen et al. (13) found that familiarity does not affect route choice behavior.

Recognizing the nature of ATIS information in dynamic environments, some analysts argued that trip choice decisions are based not only on objective information supplied by ATIS, but also on subjective information as perceived by travelers (14,15). For example, Mehndiratta et al. (16) proved that interest in travel information is a function of complex travel behavior, demographics, attitudinal characteristics, and technology interest related factors. Khattak et al. (17) concluded that commuters' diversion behavior varied with their personal characteristics and the characteristics of the trip they were making at the time when the choice arose. Mahmassani and Chen (18) concluded that there is no clear measure of information effect on travelers that is independent of user choice behavior, prevailing traffic conditions, and network interactions. Conquest et al. (19) noted that commuters provided with information from ATIS could be classified as route changers, route and time changers, non-changers, and pre-trip changers. Polak and Jones (20) found that traffic information use depends on a range of personal, travel related and contextual factors.

Methodological Background

Several methodological challenges arise to model multidimensional route choice data in the provision of real-time information. In 1980s, most discrete choice models were calibrated by the Multinomial Logit (ML) models (21). An advantage of a ML model is its analytical tractability and ease of estimation. However, A major restriction of a ML model is its competitive structure, referred to as the Independence from Irrelevant Alternatives (IIA) property, which arises because all travelers are assumed to have the same error distribution in the utility term based on a Gumbel distribution. Therefore, ML models assume independence between alternatives, which is not true when routes overlapp, and independence between observations (choices), which is not true if each subject/driver has more than one observation (choice). Several techniques have been developed to overcome the limitation of ML models.

The Nested Logit (NL) model (22) is an extension of the ML model designed to capture correlation among alternatives. It is based on the partitioning of the choice set into different nests. The NL model is designed to capture choice problems where alternatives within each nest are correlated. No correlation across nests can be captured by the NL model. When alternatives cannot be partitioned into well-separated nests to reflect their correlation, the NL Model is not appropriate. The ML model is not particularly suitable for deriving a competitive structure from data. Cascetta et al. (23) introduced the C-Logit model as a ML model that captures the correlation among alternatives in a deterministic way. They add to the deterministic part of the utility function a term, called "commonality factor", that captures the degree of similarity between the alternative and all other alternatives in the choice set. The lack of theory or guidance to which form of commonality factor should be used is a drawback of the C-Logit method. McFadden (14) presented the Cross-Nested Logit (CNL). That model is a direct extension of the NL model, where each alternative may belong to more than one nest. Similar to the NL model, the choice set is partitioned into nests. Vovsha and Bekhor (25) proposed and used a Link-Nested Logit model as an application of CNL model. The largest network they used contains one origin-destination pair, eight nodes, eleven links, and five routes. Papola (26) estimated a CNL model for intercity route choice with a limited number of alternative routes. Swait (27) proposes the Choice Set Generation Logit model, in which choice sets form the nests of a CNL structure. It was concluded that, for a realistic size network and a realistic number of links per path, the CNL model and its applications become quite complex and therefore computationally onerous.

The above models are extensions of the ML models that use a logit utility function. An alternative technique is the Multinomial Probit (MP) model. It is derived from the assumption that the error terms of the utility functions are normally distributed. It uses a probit link function instead of a logit function. MP model captures explicitly the correlation among all alternatives (mostly relative to the overlap length). Yai, et al. (21) introduced a function which represents an overlapped relation between pairs of alternatives. Estimating MP model is intractable even for a relatively low number of alternatives. Moreover, the number of unknown parameters in the variance-covariance matrix grows with the square of the number of alternatives(28). Ben-Akiva and Bolduc (29) introduced a multinomial probit model with logit kernel (or hybrid logit) model in intending to combine the advantages of logit and probit models. It is based on a utility function that has two error matrices. The elements of the first matrix are normally distributed and they capture correlation between alternatives. The elements of the second matrix are independent identically distributed. These combined models suffer from the same computational difficulties as the pure MP. In general, any application of hybrid logit or probit to a large-scale route choice case is questionable in terms of the computational effort needed for estimating the parameter coefficients and their marginal effects, especially for large networks.

The second type of correlation that transportation models may suffer from, if exists, is correlation between repeated choices made by the same traveler. In binary models, relatively few studies have accounted for the correlation between repeated observations. Abdel-Aty et al. (30) and Jou (31) addressed this issue using individual-specific random error components in binary models with a normal mixing distribution. The standard deviation of the error components were found significant in both studies. This showed clearly the need for some formal statistical corrections to account for the unobserved heterogeneity. Jou and Mahmassani (32) used a general probit model form for the dynamic switching model, allowing the introduction of state dependence and serial correlation in the model specification. In the multinomial level, Mahmassani and Liu (33) used a multinomial probit model framework to capture the serial correlation arising from repeated decisions made by the same respondent. Garrido and Mahmassani (34) used multinomial probit model with spatial and temporally correlated error structure. Chen and Jovanis (35) used mixed linear model with repeated observations to model drivers' compliance with en-route guidance.

Based on the above review, it is clear that research directed at investigating decision processes underlying route choice is not sufficiently understood. The literature is in need to a study that models travelers' realistic route choices when provided with traffic information/advice in a relatively large network. Moreover, most related analyses (with few exceptions, some of them are mentioned above) ignored the correlation between repeated decisions made by the same traveler and the correlation due to overlapping between alternatives. It has been concluded also that there is a need for more efficient and statistically approved methodologies to handle the two kinds of correlation mentioned above. In this paper, a multinomial GEE model with exchangeable correlation structure was employed and compared with the corresponding model with independent structure.

METHODOLOGY

Liang and Zeger (36) originally specified the Generalized Estimating Equations (GEEs) methodology for modeling univariate marginal distributions, such as the binomial distribution. Their methodology provides a practical method with reasonable statistical efficiency to analyze discrete and correlated data. GEEs were introduced by Liang and Zeger as an extension of the Generalized Linear Models (GLM), which are extension of traditional linear models (37). Unlike GLMs, GEEs account for the covariance structure of the repeated measures. This covariance structure across repeated observations is managed as a nuisance parameter. The GEE methodology provides consistent estimators of the regression coefficient and their variances under weak assumptions about the actual correlation. Liang and Zeger (36), Zeger et al. (38) and Liang et al. (39) provide further details on the binomial GEEs. Lipsitz et al. 40) extended the methodology to model the correlation between repeated nominal categorical responses. Two kinds of correlation could be accounted for in the modeling processes, correlation between repeated choices made by the same subject (cluster correlation) and correlation between nominal alternatives (correlation due to the overlapping between routes). This section describes the MGEEs methodology adopted for this route choice application.

Suppose a number of t repeated choices are made by subject i $(i=1,...,N)$, the total number of repeated choices for subject i is T_i, and K is the total number of alternatives available for all subjects at all observations. Two-level indicator variables can be formed as y_{ikt} where; $y_{ikt}=1$ if subject i had the choice k at time t, while $y_{ikt}=0$ if otherwise. A *(k-1)* vector $y_{it}=[y_{i1t},.....,y_{i,K-1,t}]'$ can be formed to show the choice of subject i at time t. Each subject has T_i covariate vectors x_{it} , a x_{it} vector contains all the relevant covariates including the intercept, between- and within-subject covariates. Therefore, each subject has a matrix of covariates $X_i=[x_{i1},.....,x_{iT_i}]'$ of dimension $T_i \times p$. Where p is the total number of covariates excluding the intercept.

The distribution of y_{it} is multinomial with the probability function

$$f(y_{it} \mid x_{it}, \beta) = \prod_{k=1}^{K} \pi_{ikt}^{y_i kt} \tag{1}$$

Where $\pi_{ikt} = E(y_{ikt} \mid x_{it}, \beta) = pr\{y_{ikt} = 1 \mid x_{it}, \beta\}$ is the probability that subject *i* had the choice k at time t, β is a $(p \times 1)$ vector of parameters. When y_{it} is binary, π_{ikt} is usually modeled with logistic or probit link function (36). When k>2 with non-ordered response, the generalized polytomous logit link is appropriate (40).

The matrix of coefficient parameters β is associated with the [(*K*-1) x 1] marginal probability vector

$$E(Y_{it} \mid X_i) = \pi_{it}(\beta) = [\pi_{it1}, ..., \pi_{i,(K-1),t}]' \tag{2}$$

These marginal probability victors can be grouped together to form the [$T_i(K-1)$ x 1] vector

$$E(Y_i \mid X_i) = \pi_i(\beta) = [\pi'_{i1}, ..., \pi'_{iT_i}]' \text{; where } Y_i = [Y'_{i1}, ..., Y'_{iT_i}]' \tag{3}$$

The GEEs of the following form can be used to estimate β (36,40)

$$u(\hat{\beta}) = \sum_{i=1}^{N} \frac{d[\pi_i(\beta)]'}{d\beta} \hat{V}_i^{-1} [Y_i - \hat{\pi}_i] = 0 \tag{4}$$

Where V_i is the covariance matrix of Y_i. This covariance matrix, V_i, is a function of β and other nuisance parameters α which is a function of the correlation between repeated choices made by the same subject *i*. Also, V_i depend on the correlation between overlapped (or correlated) alternative routes. This covariance matrix, V_i, has [T_i x T_i] blocks. Each block has [$(K-1)$ x $(K-1)$] elements.

Estimating V_i

To get a general form of V_i, the correlation matrix of the elements of Y_i must be developed or estimated first. Therefore, the pairwise correlation between the (*K*-1) elements of Y_{is} and Y_{it} which accounts for correlation between observations *s* and *t* of subject *i*, must be determined. A typical element of the correlation matrix of the elements of Y_i is, for any pair of response levels *j* and *k* and pair of times *s* and *t*,

$$Corr(Y_{ijs}, Y_{ikt}) = E[e_{ijs}\, e_{ikt}] \text{, where } e_{ikt} = \frac{Y_{ikt} - \pi_{ikt}}{[\pi_{ikt}(1-\pi_{ikt})]^{1/2}} \tag{5}$$

The element e_{ikt} is the residual for Y_{ikt}. This residual e_{ikt} is a typical element of the residual vector $e_{it} = A_{it}^{-1/2}[Y_{it} - \pi_{it}]$. Where A_{it} is a function of β only, then it does not depend on correlation. That is,

$$A_{it} = Diag[\pi_{i1t}(1-\pi_{i1t}), ..., \pi_{i,K-1,t}(1-\pi_{i,K-1,t})] \tag{6}$$

$$A_{it}^{-1/2} = Diag\,[(\pi_{i1t}(1-\pi_{i1t}))^{-1/2},...,(\pi_{i,K-1,t}(1-\pi_{i,K-1,t}))^{-1/2}] \quad (7)$$

The correlation matrix of $Y_i = R_i(\alpha)$ with e_{ikt} as a typical element can be written as

$$Corr(Y_i) = R_i(\alpha) = \mathrm{var}(e_i) = A_i^{-1/2}\,\mathrm{var}(Y_i)\,A_i^{-1/2} \quad (8)$$

or, $$\mathrm{var}(Y_i) = V_i = A_i^{1/2}\,Corr(Y_i)\,A_i^{1/2} \quad (9)$$

where, $\hat{e}_i = [\hat{e}_{i1},...,\hat{e}_{iT_i}]$, and $A_i = Diag[A_{i1},...,A_{iT_i}]$

Then, $\mathrm{var}(Y_i)$ depends on β and $R_i(\alpha)$ where the latter takes the effect of correlation in computing the covariance matrix $\mathrm{var}(Y_i)$. The matrix $R_i(\alpha)$ is T_i by T_i block diagonal matrix. Each block is [$(K-1)$ x $(K-1)$] matrix. The tth diagonal block of $R_i(\alpha)$ is $A_{it}^{-1/2}V_{it}\,A_{it}^{-1/2}$, also, the *sth*-row-and-*tth*-column off-diagonal block $\rho_{ist}(\alpha)$ is

$$\rho_{ist}(\alpha) = A_{is}^{-1/2}\,E[(Y_{is}-\pi_{is})(Y_{it}-\pi_{it})']\,A_{it}^{-1/2} \quad (10)$$

Where, $V_{it} = \mathrm{var}(Y_{it}) = Diag[\pi_{it}] - \pi_{it}\pi'_{it}$ and $Diag[\pi_{it}]$ denotes a diagonal matrix with elements of π_{it} on the main diagonal and zero off-diagonal elements. The diagonal blocks of $R_i(\alpha)$ depend only on $\pi_i(\beta)$. In these diagonal blocks, the diagonal elements are:

$$Corr(Y_{ikt}, Y_{ikt}) = 1 \quad (11)$$

and the off-diagonal elements are

$$Corr(Y_{ijt}, Y_{ikt}) = \frac{cov(Y_{ijt}, Y_{ikt})}{\{\pi_{ijt}(1-\pi_{ijt})\,\pi_{ikt}(1-\pi_{ikt})\}^{-1/2}} = \frac{-\pi_{ijt}\pi_{ikt}}{\{\pi_{ijt}(1-\pi_{ijt})\,\pi_{ikt}(1-\pi_{ikt})\}^{-1/2}} \quad (12)$$

Recall that these off-diagonal elements of the diagonal blocks of $R_i(\alpha)$ depend only on the t^{th} choice of subject *i* from the *K* alternatives available. Equation 12 shows the correlation structure between the different alternatives. The dimensions of this correlation structure depend on the number of alternatives *k*. This clearly takes care of any correlation between the different alternatives of the multidimensional route choice model, usually due to overlapped distances between different routes. Then, the unknown elements of $R_i(\alpha)$ are the elements of its off-diagonal blocks $\rho_{ist}(\alpha)$. It must be estimated.

If $\rho_{ist}(\alpha)$ is known, then $R_i(\alpha)$ is known, then the only unknown term in Equation 4 is β. The estimated $\hat{\beta}$ can be obtained by a fisher-scoring algorithm until convergence,

$$\widehat{\beta}^{m+1} = \widehat{\beta}^{m} + \left[\sum_{i=1}^{N} \frac{d[\pi_i(\widehat{\beta}^m)]}{d\beta} \left(\widehat{\beta}^m\right)' \left[V_i\left(\widehat{\beta}^m, \widehat{\alpha}^m\right)\right] \right]^{-1} \left[\frac{d[\pi_i(\widehat{\beta}^m)]}{d\beta} \widehat{\beta}^m \right]^{-1}$$
$$* \sum_{i=1}^{N} \frac{d[\pi_i(\widehat{\beta}^m)]}{d\beta} \left(\widehat{\beta}^m\right)' \left[V_i\left(\widehat{\beta}^m, \widehat{\alpha}^m\right)\right]^{-1} \left[Y_i - \pi_i\left(\widehat{\beta}^m\right)\right], \quad (13)$$

where *m* is the iteration number. A starting β can be obtained by applying the regular ML model. Iteration should continue until $\widehat{\beta}^{m+1} = \widehat{\beta}^{m}$ and $\widehat{\alpha}^{m+1} = \widehat{\alpha}^{m}$. Where $\widehat{\alpha}^{m}$ is the estimated $\rho_{ist}(\alpha)$ in the m^{th} step.

Estimating $\rho_{ist}(\alpha)$

Zeger and Liang (36) proposed the exchangeable correlation structures that can be assumed and used in the binary models. This structure assumes equal correlation between repeated choices made by a subject. Lipsitz et al. (40) extended the same structure for the multidimensional models where any two observations on the same subject *i* and category *k* are equally correlated. Under this assumption, $\rho_{ist}(\alpha)$ can be estimated as

$$\widehat{\alpha} = \rho_{ist}(\widehat{\alpha}) = \frac{\sum_{i=1}^{N}\sum_{t>s} \widehat{e}_{is}\widehat{e}'_{it}}{\left[\sum_{i=1}^{N} 0.5 T_i (T_i - 1)\right] - p} \quad (14)$$

where p is the total number of independent variables including any interactions. The residual vector $\widehat{e}_{it} = \widehat{A}_{it}^{-1/2}[Y_{it} - \widehat{\pi}_{it}]$, which is estimated by plugging $\widehat{\beta}$ from a previous step of iteration into A_{it} *and* π_{it}. It is worth mentioning that the elements of the correlation matrix $\rho_{ist}(\alpha)$ do not depend on the times s and t, but they do depend on the levels j and k.

SUBJECT RECRUITMENT AND DATA COLLECTION

Subjects were recruited from the University of Central Florida (UCF) using an experimental design based on their age and gender. They included faculty, staff, graduate and undergraduate students. In this paper, the driver characteristics that were investigated include gender, age, income, level of education, and driving experience. Students were chosen to represent low income, young, less driving experience, and moderate level of education. Faculty members were chosen to represent high level of education and high income level. Staff members were chosen to fill up the empty cells in the experimental design as they include high range of age, income and driving experience. In addition, the authors meant to recruit all subjects from UCF (which is the destination of the network used) to be their real destination in their morning commute trips. About 12% of the subjects were in their first 2 weeks of attending UCF, representing non-familiar travelers. While we acknowledge that the sample is not a random sample of the population due to funding limitations, as mentioned above a concerted effort was curried out to obtain a representative sample based on an experimental design from UCF (40,000 student population + 2000 faculty and staff).

Subjects were instructed that their main task is to minimize the overall trip travel time by deciding when and when not to follow the information and/or advice provided. Subjects have been asked not to go through the simulation unless they had at least 30 minutes of spare time (the average simulation time was found to be 23.77 minutes) and were willing to concentrate and do their best in their choices. Moreover, during the simulation, the subjects' response time was measured without notifying them, to insure that they are serious. A total of 65 subjects had run the simulation. Two subjects out of the 65 have been excluded from this study because their response time were found outliers in the normal distribution plotting of subjects' response time (Z=3.21 and 3.78, Zcr = 2.57).

DATA DESCRIPTION

A total of 630 trial days (trips) have been completed by the 63 qualified subjects. Out of these 630 trial days, 539 were in the drive mode, where the analysis of this paper focuses, and 91 were in the transit (bus) mode. In OTESP, the subject is required to make 10 morning home-to-work trips from the origin (assumed home) to the destination (UCF) under five different scenarios (levels of ATIS), two trial days per each scenario. The 539 routes of these trips were identified and categorized by the sequence of links that were traversed on a given trip. The chosen routes were ranked and numbered by their frequency of use. These numbers were used as routes' IDs. The results showed that 44 distinct routes have been chosen during the 539 experimental trial days. Table 1 shows the sequence of links of the 44 chosen routes and their frequency of use.

The network used consists of mainly four east-west arterials that take the driver from the origin to the destination. Five minor arterials and local collectors allow the driver to divert from one main arterial to another. The four main arterials are named MA1, 2, 3 and 4. The remaining analysis of this paper considers these four main arterials together form the choice set that was available to all subjects in all 539 trial days of this analysis. MA1 is physically the aggregation of two chosen routes, chosen route #1 and 2. Both of these two chosen routes consist mainly from expressway links. Therefore, MA1 represents the expressway alternative on the network. The other three main arterials MA2, MA3, and MA4 are physically coinciding with the chosen routes # 3, 7, 9, respectively. MA2 is a 6-lane arterial while MA3 is a 4-lane arterial with relatively high number of traffic lights. MA4 is a rural 2-lane 2-way arterial with speed limit that is approximately equal to those of MA2 and MA3. MA1 has the higher speed limit among the four alternatives with few traffic lights because it consists mainly from expressway links.

The 44 chosen routes of this study were aggregated to the above four main arterials. A chosen route was situated to a certain main arterial if and only if the chosen route overlaps with this main arterial in a longer distance than does it with any of the other three main arterials. For example, the chosen route # 24 belongs to MA2 because the former overlaps with the latter in links # 19, 20, 21, and 39, where the summation distance of these four links are greater than the overlapping distance between the chosen route # 24 and any of MA1, MA3 or MA4.

Based on historical volumes and an algorithm (2, 3), the simulator calculates the speed of every link for every movement on the network (each link has its own normal distribution from which this link's travel time is chosen). When the subject moves from a node to another all the links' travel times are updated. The simulator saves to a database the travel time of all 40 links of the network every time the subject moves from a node to another.

In the analysis phase, and after identifying the 44 distinct chosen routes, the travel time of these 44 routes were computed for every trial day. One of the 44 travel time values represents the actual travel time of the subject on that trial day. The other 43 travel time values represent what would have been the travel time for that trial day if the subject had chosen one of the other 43 routes. As for the four main arterials, the travel time was calculated as the average of all the routes that constitute each arterial. The travel time of the chosen arterial was taken as that of the actual chosen route.

The simulator provided five different levels or scenarios of ATIS to the subjects including: no information (scenario #1), pre-trip information with and without advice (scenarios #2 and #3, respectively), and en-route information (in addition to the pre-trip information) with and without advice (scenarios #4 and #5, respectively). Therefore, in 80% of the trial days (scenarios 2 to 5), all links' level of congestion was shown to the subjects in quantitative (travel time) and qualitative (green, yellow, red links for free flow, moderate, congested links, respectively). In addition, in 40% of the trial days (scenarios 4 and 5), subjects are provided with the travel-time-based shortest route as an advice. Figure 2 shows the average travel times of the 539 trial days categorized by the scenario of each trial day and the main arterial to which the chosen route is belonging to. On average, MA1 had the least travel times on the network because it represents the only expressway links on the network. Scenario 1 had the highest travel times where no information was provided to the subjects. On the other hand, Figure 2 shows that the average travel time is gradually reduced with the increase of the level of information/advice provided (scenarios 2 to 5). This proves the benefits of providing traffic information to drivers in reducing travel time. Among the four main arterials, MA1 (expressway links) had the least variation in the travel time between the five different scenarios of ATIS. This means that the gain from providing traffic information to drivers is higher for the non-expressway links than the expressway ones. This showed that drivers diverted easily or more frequently from non-expressway links to the advised route and saved travel time. While, those who were driving on expressway links and advised to an alternative route were less likely to divert.

MULTINOMIAL ROUTE CHOICE MODELING

The proposed multinomial GEE method with generalized polytomous logit function was employed to model correlated route choices. The categorical dependent variable has four alternatives, MA1, MA2, MA3, and MA4. These four alternatives form the fixed choice set that was available for all subjects at all trial days. The reference alternative for which all attributes in the analysis are set equal to zero is MA4. This was decided because this main arterial had the least frequency over the other three main arterials (Table 1). The dependent variable takes on a value of 1 to 4. The observed distribution of the dependent variable is shown in Table 1. The independent variables include:

1. Age; “1” if subject’s age > 30, “0” otherwise
2. Income; “1” if household income > $65,000, “0” otherwise
3. Education; “1” if graduate school or higher, “0” otherwise
4. Shortest 1; “1” if MA1 was the shortest path, “0” otherwise
5. Shortest 2; “1” if MA2 was the shortest path, “0” otherwise
6. Shortest 3; “1” if MA3 was the shortest path, “0” otherwise
7. Advised 1; “1” if MA1 was the shortest path and the trial day was under scenario #3 or #5 (i.e., MA1 was given as advice), “0” otherwise
8. Advised 2; “1” if MA2 was the shortest path and the trial day was under scenario #3 or #5 (i.e., MA2 was given as advice), “0” otherwise
9. Advised 3; “1” if MA3 was the shortest path and the trial day was under scenario #3 or #5 (i.e., MA3 was given as advice), “0” otherwise
10. Travel time 1; Travel time of MA1
11. Travel time 2; Travel time of MA2
12. Travel time 3; Travel time of MA3
13. Travel time 4; Travel time of MA4

Table 2 and Table 3 show the modeling results using the multinomial GEE model for the independent case (no correlation is considered) and for the proposed exchangeable correlation, respectively. The differences in the results are due to the effect of correlation. By comparing the overall and model-minus-intercept F-statistic values for the two models, the exchangeable model was favored over the independent model (compare 83417.09 vs. 11464.98; 58572.64 vs. 49970.90). The number of degrees of freedom that were used for the overall model in the independent and exchangeable models were 42 and 43, respectively. The decrease was one degree of freedom that was used in estimating the fixed exchangeable correlation between any two choices made by the same subject and had the same alternative. The model does not predict but computes and incorporates the correlation between two choices with different alternatives, mostly due to the overlapping distance between them, in the variance-covariance matrix of the dependent variable as discussed in the methodology part of this paper. The model came up with three logistic equations for the four alternatives (MA1 vs. MA4; MA2 vs. MA4, MA3 vs. MA4). These equations are:

$$\log\left(\frac{\hat{\pi}_{MA1}}{\hat{\pi}_{MA4}}\right) = -65.12 + 3.42\,age + 2.36\,Income + 5.00\,Education + 22.15\,S1 + 11.65\,S2 + 13.23\,S3 \\ + 5.56\,A1 - 4.70\,A2 - 4.87\,A3 - 6.00\,TT1 - 2.35\,TT2 - 0.67\,TT3 + 9.56\,TT4$$

$$\log\left(\frac{\hat{\pi}_{MA2}}{\hat{\pi}_{MA4}}\right) = -35.39 + 2.41\,age + 1.01\,Income + 1.99\,Education + 21.62\,S1 + 12.17\,S2 - 7.01\,S3 \\ + 26.60\,A1 - 11.34\,A2 - 25.95\,A3 - 4.28\,TT1 - 2.18\,TT2 - 0.36\,TT3 + 7.36\,TT4$$

$$\log\left(\frac{\hat{\pi}_{MA1}}{\hat{\pi}_{MA4}}\right) = -3.63 + 9.38\,age + 2.49\,Income + 12.37\,Education - 10.49\,S1 - 48.61\,S2 + 22.67\,S3 \\ + 3.69\,A1 - 44.56\,A2 + 1.41\,A3 - 0.79\,TT1 - 0.10\,TT2 - 1.00\,TT3 + 1.89\,TT4$$

Where the symbols *Sx*, *Ax*, and *TTx* refer to the effects “Shortest x”, “Advised x”, and “Travel time x”, respectively where x is the main arterial number. Using the above equations, the probability of choosing an alternative given a set of values for the independent variables is simple compared to using any probit link function (probit models). Moreover, computing a certain marginal effect of any variable on choosing an alternative is straightforward and simple regardless of the number of alternatives used in the model, which is not the case for the corresponding multinomial probit models. In the above equations, exponentiating the estimated regression coefficient yields the odds of choosing the corresponding alternative vs. choosing the base alternative MA4 for each one-unit increase in the corresponding explanatory variable. For example, the ratio of odds for a one-unit change in the travel time of MA2 is equal to $e^{-2.18} = 0.11$. This shows the ease of this model compared to the corresponding probit models.

Table 2 and Table 3 show the parameter coefficients for each equation with the corresponding t-statistic of each effect. Table 2 and Table 3 show also the F-statistic for each effect in the overall MGEE model. These values show the individual significance of every effect in the overall model and determine if changing the value of this effect statistically changes the probability of choosing a certain alternative or not. A certain effect may show up as significant in an equation while show up as insignificant effect in another equation. All the 13 effects included were found significant. The parameters' coefficients in Table 3 show that older drivers (>30), those with high household incomes, and those with high level of education are, in general, more likely to choose MA1, MA2, or MA3 than MA4, i.e., they are more likely to choose the expressways and/or the multilane arterials. Recall, MA4 is a 2-lane 2-way rural arterial. However, the increase in this likelihood in some cases is not statistically significant. For example, these above three socioeconomics do not affect the probability of choosing MA2 vs. MA4 (t-statistics = 1.07, 0.45, 0.74 < 1.96).

The three effects "Shortest 1", "Shortest 2", and "Shortest 3" measure the effect of providing information without advice to the subjects. The significance of the effect "Shortest 1" in the first equation with a positive coefficient parameter (22.15) shows that the probability of choosing the first alternative MA1 increases if this route is the travel-time-based shortest route on the network, even with providing advice-free information. This means that the subjects were able to use and benefit from the qualitative and quantitative information provided to them. Moreover, they might be able to identify and then use the shortest route themselves using the travel times given to them. The same interpretation goes to the coefficient parameters of the effects "Shortest 2" and "Shortest 3" in Equations 2 and 3, respectively. By comparing these three coefficients (22.15, 12.17, 22.67), differences were noticed. This indicates that the marginal effects of these variables are not the same. However, they measure the same independent variable for different alternatives. Then, it can be concluded that providing traffic information to drivers increases the likelihood of choosing the shortest path (identified by them or given to them by the information system) but with odds different from shortest path to another depending on its own characteristics.

To measure the effect of advising a certain arterial in addition to providing traffic information on all links of the network to the subjects, the three effects "Advise 1", "Advise 2", and "Advise 3" were employed. Advising MA1 or MA2 to the subjects increased their likelihood to be chosen (coefficients of 29.60 and 11.34, respectively). While, advising MA3 as the shortest path for a certain trial day does not affect its probability of being chosen (t-statistic = 0.24). This was not surprising because MA3 is well known by its regular congestion due to its high accessibility and high number of traffic lights. Recall, in this study, most of the subjects were familiar with the network. Similar to the effect of information without advice, the coefficient parameters "Advised 1" in equation 1, "Advised 2" in equation 2, and "Advised 3" in equation 3 (29.60, 11.34, 0.00) show that advising a certain route to the drivers may and may not increase its likelihood to be chosen depending on the characteristics of the route itself. In this analysis, advising expressway or 6-lane arterials increased their likelihood to be chosen (MA1 and MA2). While advising 4-lane arterial with high density of traffic lights did not affect its likelihood to be chosen. Then it can be concluded that the characteristics of a certain route affects its likelihood to be chosen if advised to drivers.

The effect of the travel time was represented in this model by the variables TT1, TT2, TT3, and TT4. The first three effects hold negative coefficients in the three equations with significant effect for TT1 in equation 1, TT2 in equation 2, and TT3 in equation 3. This clearly shows that the probability of choosing a certain route decreases when its travel time increases. The effect TT4, the travel time of the base route MA4, showed up as a positive significant variable in the three equations. Therefore, the probability of choosing the other route (not choosing this base route) increases with increasing the travel time of the base alternative.

CONCLUSIONS

This paper modeled multinomial route choice under ATIS using correlated data. A travel simulator was used as a data collection tool. A relatively large realistic network was used. Traffic information with and without advice was provided to 63 subjects who have completed 539 trial days. Forty-four distinct routes were chosen. Correlation between repeated choices made by the same individual and/or between routes that have overlapping distance was considered. Multinomial Generalized Estimating Equations (MGEEs) methodology was proposed and used with generalized polytomous function and exchangeable correlation structure to insure validity of statistical models. The resulting model was compared with a similar independent model (without correlation structure). The proposed model was favored over the independent model. The analysis showed that the travel-time gain by providing traffic information is higher for non-expressway than expressway routes. The modeling results showed that the subjects were able to use and benefit from the qualitative and quantitative information provided to them. Moreover, they might be able to identify the shortest route themselves using the travel times given to them. It was also concluded that the odds of choosing a certain shortest route (advised or recognized by drivers using the advice-free traffic information provided) varies from route to another and depends on the characteristics of the route itself. For example, the analysis of this paper showed that advising expressway or 6-lane arterials increases their likelihood to be chosen (MA1 and MA2). While advising 4-lane arterial with high density of traffic lights does not affect its likelihood to be chosen. The paper addresses the benefits and use of ATIS in route choice in a microscopic level (one driver at a time). Future work should address the issue of market penetration which will likely affect the performance of the network. This paper underlines the importance of modeling correlation in the multinomial route choice models. The proposed model proved to account for correlation in the multinomial repeated route choices with simple computational effort compared to the existing methodologies.

REFERENCES

1. Pallottino, S. and Grazia, M. (1988) "Shortest Path Algorithms in Transportation Models: Classical and Innovative Aspects" In P. Marcotte and S. Nguyen, editors, *Equilibrium and Advanced Transportation Modeling*, pp. 245-28.
2. Abdel-Aty, M. and Abdalla, F. (2002a) "Design and Development of a Computer Simulation Tool to Collect Data that Support Hybrid Travel Models under ATIS" Proceedings of the Annual Conference of the Canadian Society for Civil Engineering, Montreal, Quebec, Canada.
3. Abdel-Aty, M. and Abdalla, F. (2002b) "A Computer Simulation and Animation Tool for Travel Data Collection" Submitted to the Journal Transportation Engineering, ASCE.
4. Delvert, K. (1997) "Heterogeneous Agents Facing Route Choice: Experienced versus Inexperienced Tripmakers." Presented at IATBR '97, Austin, TX.
5. Gopinath, D. (1995) "Modeling Heterogeneity in Discrete Choice Processes: Application to Travel Demand" MIT, Ph.D. Thesis.
6. Polydoropoulou, A., Ben-Akiva, M., Khattak, A., and Lauprete, G. (1996) "Modeling Revealed and Stated En-Route Travel Response to Advanced Traveler Information Systems" Transportation Research Record, vol. 1537.
7. Khattak, A., Polydoropoulou, A., and Ben-Akiva, M. (1996) "Modeling Revealed and Stated Pretrip Travel Response to Advanced Traveler Information Systems" Transportation Research Record, vol. 537.
8. Abdel-Aty, M., Vaughn, K., Kitamura, R., Jovanis, P., and Mannering, F. (1994) "Models of Commuters' Information Use and Route Choice: Initial Results Based on Southern California Commuter Route Choice Survey" Transportation Research Record, vol. 1453, pp. 46-55.
9. Kim, K., and Vandebona, U. (2002) "Understanding Route Change Behavior – A Commuter Survey in South Korea" Presented at Transportation Research Board. 81st Annual Meeting. Washington, D.C.
10. Lotan, T. (1997) "Effects of Familiarity on Route Choice Behavior in The Presence of Information" Transportation Research, Part C, Vol. 5, pp. 225-243.
11. Adler, J. and McNally, M. (1994) "In-Laboratory Experiments to Investigate Driver Behavior under Advanced Traveler Information Systems" Transportation Research, 2C, pp. 149-164.
12. Bonsall, P., and Parry, T. (1991) "Using an Interactive Route-Choice Simulator to Investigate Driver's Compliance with Route Guidance Advice" Transportation Research Record, vol. 1306, pp. 59-68.
13. Allen, R., Ziedman, D., Rosenthal, T., Stein, A., Torres, J., and Halati, A. (1991) "Laboratory Assessment of Driver Route Diversion in Response to In-Vehicle Navigation and Motorist Information Systems" *Transportation Research Record*, vol. 1306, pp. 82-91.
14. Ben-Akiva, M., De-Palma, A., and Kaysi, I. (1991) "Dynamic Network Models and Driver Information Systems" Transportation Research A, vol. 25, pp. 251-266.
15. Zhao, S., Harata, N., and Ohta, K. (1996) "Assessing Driver Benefits from Information Provision: A Logit Model Incorporating Perception Band of Information" Proceedings of the 24th annual Passenger Transport Research Conference, London, England.
16. Mehndiratta S., Kemp M., Lappin J., and Nierenberg, E. (2000) "Who are the Likely Users of ATIS? Evidence from the Seattle Region" Presented at the *Transportation Research Board* 79th Annual Meeting. Washington, D.C.
17. Khattak, A, Schofer, J., and Koppelman, F. (1993) "Commuters' En-route Diversion and Return Decisions: Analysis and Implications for Advanced Traveler Information Systems" *Transportation Research Record*. vol. 24A, pp. 101-111.
18. Mahmassani, H. and Chen, P. (1993) "An Investigation of the Reliability of Real-Time Information for Route Choice Decisions in a Congested Traffic Network System" Transportation, Vol. 20, pp. 157-178.
19. Conquest, L., Spyridakis, J., and Haselkorn, M. (1993) "The Effect of Motorist Information on Commuter Behavior: Classification of Drivers into Commuter Groups" Transportation Research C, Vol. 1, pp. 183-201.
20. Polak J. and Jones P. (1995) "The Acquisition of Pre-Trip Information: A Stated Preference Approach" Transportation 20, pp. 179-198.
21. Yai, T., Iwakura, S and Morichi, S. (1997) "Multinomial Probit with Structured Covariance for Route Choice Behavior." *Transportation Research*, 31B, 3, 195-207.
22. Ben-Akiva, M. E. (1973). Structure of passenger travel demand models, PhD thesis, Department of Civil Engineering, MIT, Cambridge, Ma.

23. Cascetta, E., Nuzzolo, A., Russo, F., and Vitetta, A. (1996) "A Modified Logit Route Choice Model Overcoming Path Overlapping Problems: Specification and Some Calibration Results for Interurban Networks." Transportation and Traffic Theory. Proceedings from the 13th International Symposium on Transportation and Traffic Theory, Lyon, France.
24. McFadden, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration, Econometrica 57(5): 995–1026.
25. Vovsha, P. and Bekhor, S. (1998) "The Link-Nested Logit Model of Route Choice: Overcoming the Route Overlapping Problem." *Transportation Research Record*, 1645, 133.
26. Papola A. (2000) "Some Development of the Cross-Nested Logit Model." *Proceedings of the 9th IATBR Conference*, Gold Coast, July 2000.
27. Swait, J. (2001) "Choice Set Generation within the Generalized Extreme Value Family of Discrete Choice Models" *Transportation Research*, 35B, 643-666.
28. McFadden, D. (1989) "A method of simulated moments for estimation of discrete response models without numerical integration" Econometrica 57(5): 995–1026.
29. Ben-Akiva, M. E. and Bolduc, D. (1996). Multinomial probit with a logit kernel and a general parametric specification of the covariance structure, presented at the 3rd International Choice Symposium, Columbia University.
30. Abdel-Aty, M., Kitamura, R., and Jovanis, P. (1997) "Using Stated Preference Data For Studying The Effect of Advanced Traffic Information on Drivers' Route Choice" Transportation Research, Part C, Volume 5.
31. Jou, R. (2001) "Modeling the impact of pre-trip information on commuter departure time and route choice" *Transportation Research, Part B*, 35, pp. 887-902.
32. Jou, R. and Mahmassani, H. (1998) "Day-To-Day Dynamics of Urban Commuter Departure Time and Route Switching Decisions: Joint Model Estimation" Travel Behavior research, New York: Elsevier.
33. Mahmassani, H. and Liu, Y. (1998) "Dynamics of Commuting Decision Behavior under Advanced Traveler Information Syatems" *Transportation Research*, Part C, Vol. 7, Issue 2, pp. 91-107.
34. Garrido, R. and Mahmassani, H. (2000) "Forecasting Freight Transportation Demand with the Space-Time Multinomial Probit Model" Transportation Research, Part B, Vol. 34, Issue 5, pp 403-418.
35. Chen, W. and Jovanis, P. (2003) "Analysis of Driver En-Route Guidance Compliance and Driver with ATIS using a Travel Simulation Experiment", presented at the 81st Transportation Research Meeting. Washington, DC.
36. Liang, K. and Zeger, S. (1986) "Longitudinal Data Analysis using Generalized Linear Models" Biometrika, 73, 13 -22.
37. Nelder, J. and Wedderburn, R. (1972) "Generalized Linear Models" Journal of the Royal Statistical Society, A, 135, 370 -384.
38. Zeger, S., Liang, K., and Albert, P. (1988) "Models for Longitudinal Data: A Generalized Estimating Equation Approach" Biometrics, 44, 1049-1060.
39. Liang, K., Zeger, S., and Qaqish, B. (1992) "Multivariate Regression Analysis for Categorical Data" Journal of Royal Statistical Society, Series B, 54, 30-40.
40. Lipsitz, S., Kim, K., and Zhao, L. (1994) "Analysis of Repeated Categorical Data Using Generalized Estimating Equations" *Statistics in Medicine*, 13, 1149 -1163.

Table 1. The Chosen Routes and the Main arterials

Chosen-Route	Links	Frequency	Main Arterial	Frequency
R1	22,5,6,29,35,19,20,21,39	168	Main arterial 1 (MA1)	374
R2	22,5,6,7,8,9,10,40	77		
R4	22,5,6,7,8,9,32,38,39	43		
R5	22,5,6,7,8,31,37,21,39	33		
R6	22,5,28,12,35,19,20,21,39	20		
R12	22,5,6,7,30,36,20,21,39	8		
R15	22,5,6,29,13,14,37,21,39	7		
R20	22,5,6,7,30,14,37,21,39	4		
R21	22,5,6,7,8,9,10,16,38,39	3		
R27	22,5,6,29,13,36,20,21,39	2		
R28	22,5,6,7,8,31,15,16,40	2		
R33	22,5,28,28,6,7,8,9,32,38,39	1		
R34	22,5,6,7,8,9,32,32,10,40	1		
R35	22,5,6,7,8,31,15,38,39	1		
R38	1,23,28,28,6,7,8,31,37,21,39	1		
R39	1,23,6,7,30,14,37,21,39	1		
R40	22,27,33,17,18,35,13,36,20,21,39	1		
R41	22,5,28,28,6,7,8,9,10,40	1		
R3	22,27,33,17,18,19,20,21,39	60	Main Arterial 3 (MA2)	99
R8	1,23,28,34,18,19,20,21,39	12		
R13	22,27,11,34,18,19,20,21,39	7		
R14	22,5,28,34,18,19,20,21,39	7		
R19	22,5,28,12,13,36,20,21,39	5		
R22	22,27,11,12,35,19,20,21,39	3		
R24	1,23,28,12,35,19,20,21,39	2		
R29	1,23,6,7,30,36,20,21,39	1		
R31	22,5,6,7,8,9,32,16,40	1		
R37	1,23,28,12,13,36,20,21,39	1		
R7	22,27,11,12,13,14,15,38,39	12	Main Arterial 3 (MA3)	37
R11	22,27,11,12,13,14,37,21,39	8		
R16	22,5,28,12,13,14,37,21,39	6		
R18	22,27,11,12,13,36,20,21,39	5		
R23	1,23,28,12,13,14,37,21,39	2		
R26	22,5,6,29,13,14,15,38,39	2		
R30	22,5,6,29,13,14,15,16,40	1		
R36	1,23,28,12,13,14,15,38,39	1		
R9	1,2,3,4,26,32,38,39	9	Main Arterial 4 (MA4)	29
R10	1,2,24,30,36,20,21,39	9		
R17	1,2,3,25,31,37,21,39	5		
R25	1,2,3,4,26,10,40	2		
R32	1,2,24,30,14,37,21,39	1		
R42	1,2,24,8,9,32,38,39	1		
R43	1,2,24,8,9,10,40	1		
R44	1,2,24,8,31,15,38,39	1		
	Total	539	Total	539

Table 2. Modeling Results for the Multinomial GEE Without Correlation Structure

	Equation 1		Equation 2		Equation 3	
	MA1 Vs. MA4		MA2 Vs. MA4		MA3 Vs. MA4	
Parameter	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	-41.31	-12.17	-24.93	-8.14	6.02	1.64
Age	0.04	1.15	0.42	0.55	6.70	5.50
Income	2.27	3.42	3.85	4.50	2.44	2.98
Education Level	0.22	0.21	-2.36	-1.26	8.73	7.01
Shortest 1	12.71	9.92	13.37	10.64	-18.65	-17.52
Shortest 2	11.65	9.84	13.07	10.23	-23.48	-12.32
Shortest 3	1.65	1.83	-7.66	-5.63	22.67	16.71
Advised 1	7.93	9.24	21.79	16.86	3.69	3.67
Advised 2	7.26	5.12	12.95	8.22	-6.38	-2.98
Advised 3	-6.81	-7.04	-18.10	-11.33	1.41	1.35
Travel Time 1	-6.07	-24.52	-4.35	-11.27	-0.89	-10.73
Travel Time 2	-2.34	-19.66	2.23	-20.18	-0.17	-2.82
Travel Time 3	-0.67	-19.72	-0.36	-5.89	-0.96	-18.87
Travel Time 4	9.44	26.15	7.36	13.34	1.89	22.90

Overall Summary Statistics

	D.O.F	F-stat
Overall model	**42**	**11464.98**
Model minus intercept	39	**4970.90**
Intercept	3	80.11
Age	3	12.10
Income	3	7.96
Education Level	3	20.44
Shortest 1	3	197.39
Shortest 2	3	117.23
Shortest 3	3	167.53
Advised 1	3	96.60
Advised 2	3	44.95
Advised 3	3	57.78
Travel Time 1	3	202.42
Travel Time 2	3	151.75
Travel Time 3	3	400.09
Travel Time 4	3	478.48

Table 3. Modeling Results for the Multinomial GEE with Exchangeable Correlation Structure

	Equation 1		Equation 2		Equation 3	
	MA1 Vs. MA4		MA2 Vs. MA4		MA3 Vs. MA4	
Parameter	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Intercept	-65.12	-3.80	-35.39	-1.89	-3.63	-0.29
Age	3.42	2.56	2.41	1.07	9.38	3.87
Income	2.36	1.12	1.01	0.45	2.49	1.69
Education Level	5.00	2.43	1.99	0.74	12.37	4.48
Shortest 1	**22.15**	**2.74**	21.62	3.51	-10.49	-1.62
Shortest 2	11.65	2.12	**12.17**	**3.56**	-48.61	-12.12
Shortest 3	13.23	5.04	-7.01	-3.13	**22.67**	**6.57**
Advised 1	**29.60**	**3.85**	5.56	0.76	3.69	0.67
Advised 2	-4.70	-1.22	**11.34**	**3.79**	-44.56	-10.03
Advised 3	-4.87	-0.64	-25.95	-2.98	**1.41**	**0.24**
Travel Time 1	-6.00	-8.80	-4.28	-4.04	-0.79	-3.33
Travel Time 2	-2.35	-5.61	-2.18	-6.03	-0.10	-0.67
Travel Time 3	-0.67	-3.58	-0.36	-2.31	-1.00	-5.14
Travel Time 4	9.56	7.03	7.36	3.99	1.89	3.24

Overall Summary Statistics

	D.O.F	F-stat
Overall model	**43**	**83417.09**
Model minus intercept	40	**58572.64**
Intercept	3	22.05
Age	3	10.31
Income	3	2.21
Education Level	3	10.93
Shortest 1	3	79.65
Shortest 2	3	703.45
Shortest 3	3	57.34
Advised 1	3	21.51
Advised 2	3	48.55
Advised 3	3	19.91
Travel Time 1	3	100.18
Travel Time 2	3	36.34
Travel Time 3	3	15.8
Travel Time 4	3	81.22

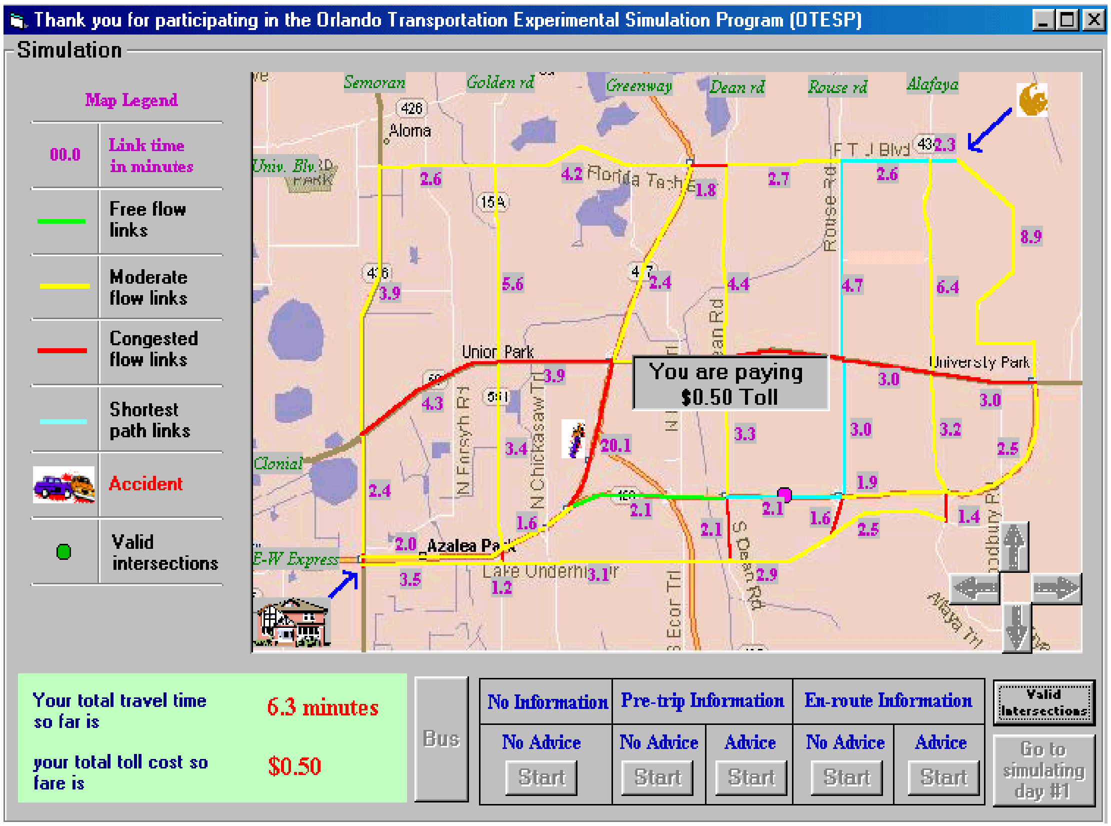

Figure 1. A Spot view for OTESP (shown is scenario #5)

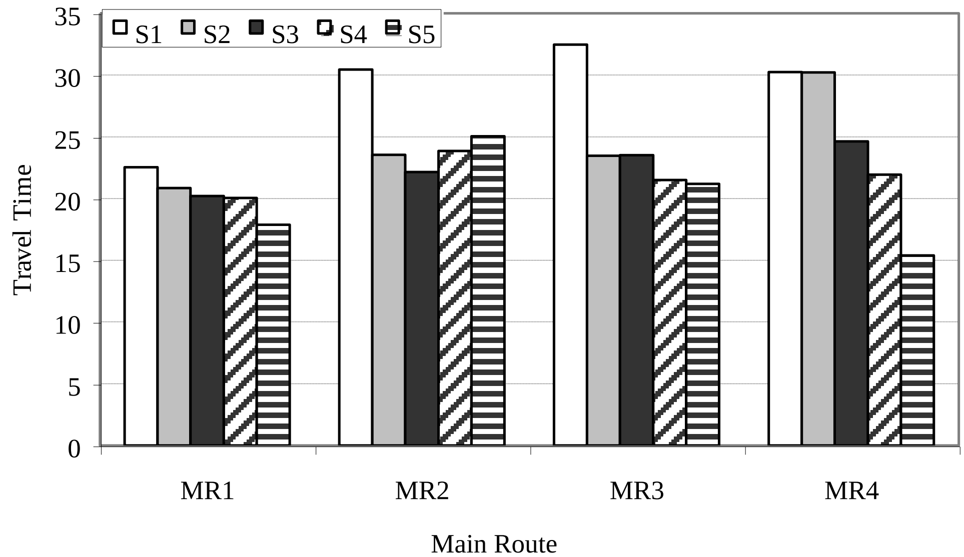

Figure 2. Average travel time for the main arterials categorized by the 5 scenarios.