CU-14-RU6899

Technical Solutions to Overcrowded Park and Ride Facilities

FINAL REPORT
February 2004

Submitted
by

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In cooperation with

New Jersey
Department of Transportation
Division of Research and Technology
and
U.S. Department of Transportation
Federal Highway Administration
and
The University Transportation Research
Center for Region II
and
The Transportation Information and
Decision Engineering Center at NJIT

Disclaimer Statement

TECHNICAL REPORT STANDARD TITLE PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
CU-14-RU6899		

4. Title and Subtitle	5. Report Date / 6. Performing Organization Code
Technical Solutions to Overcrowded Park and Ride Facilities	5. Report Date: February 2004 6. Performing Organization Code: CAIT/Rutgers
7. Author(s) Dr. Maria Boile	8. Performing Organization Report No. CU-14-RU6899
9. Performing Organization Name and Address Center for Advanced Infrastructure & Transportation (CAIT) Civil & Environmental Engineering Rutgers, The State University Piscataway, NJ 08854-8014	10. Work Unit No. 11. Contract or Grant No.
12. Sponsoring Agency Name and Address U.S. Department of Transportation Research and Special Programs Administration 400 7th Street, SW Washington, DC 20590-0001	13. Type of Report and Period Covered Final Report 14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

This report presents two transportation models that could be used for modeling park and ride intermodal travelers. The first model developed is a static intermodal-planning model that was developed for the New Jersey I80 transportation corridor and incorporated a set of the P&R facilities that are in the vicinity of the I80 Interstate Highway. This static model was based on the existing transportation-planning model currently used by the North Jersey Transportation Planning Authority (NJTPA) for North Jersey.

17. Key Words	18. Distribution Statement
Traffic capacity, traffic management centers, park and ride, ridesharing	

19. Security Classif (of this report)	20. Security Classif. (of this page)	21. No of Pages	22. Price
Unclassified	Unclassified	91	

Form DOT F 1700.7 (8-69)

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Abstract

This report presents two transportation models that could be used for modeling park and ride intermodal travelers. The first model developed is a static intermodal-planning model that was developed for the New Jersey I80 transportation corridor and incorporated a set of the P&R facilities that are in the vicinity of the I80 Interstate Highway. This static model was based on the existing transportation-planning model currently used by the North Jersey Transportation Planning Authority (NJTPA) for North Jersey. The principal characteristics of this model are:

- The model considers the following person-trips: auto only, transit only and intermodal (auto plus transit).
- It is assumed that a static Origin Destination (OD) matrix is known for all persons.
- The model assumes steady state conditions for the analysis period.
- All travelers have full information of the traffic conditions and they use the User Equilibrium (UE) traffic assignment principle to choose their OD paths.
- A set of link travel cost functions is known.
- The intermodal traffic assignment model produces the UE paths for all persons.

The main *deficiencies* of static intermodal planning models are:

- They cannot be used for congested conditions since the monotonicity of the link travel cost functions is violated.
- It cannot model adequately the impact of traffic signal timing.
- It cannot model adequately link interactions.
- The traffic demand is dynamic in nature.

The second model is based on a simulation-based dynamic traffic assignment that overcomes some of the deficiencies identified earlier such as:

- The OD matrix is dynamic. It is based on a discretization of the time into small intervals. This discretization is usually based on the traffic flow profile of traffic counts. Its accuracy depends on the availability of traffic counts on the network links, the spatial distribution of the locations of the traffic counts and the aggregation of the traffic counts. The most frequent aggregation of the traffic counts is 15-minute time intervals. A smaller time interval such as 5 minutes would be much more preferable as it will give a much better

representation of the traffic flow dynamics and lead to a more representative DTA model.

- The traffic is modeled according to a traffic simulator that incorporates the proper geometry and traffic signal timing, which can model both, congested (oversaturated) and uncongested traffic conditions. The traffic simulator could be used at either the microscopic or mesoscopic level. At the microscopic level it models the actual vehicle dynamics and driver instantaneous decisions whereas at the mesoscopic level vehicles follow the macroscopic relationships of the traffic flow theory (flow-speed-density) while each vehicle is monitored and modeled along its chosen OD path. Under microscopic modeling, traffic moves at a sub-second time interval that is user defined. Under the mesoscopic modeling traffic moves every few seconds, although it could be set also at the sub-second time interval.

The principal uses of the intermodal-planning model are:

- Evaluation of infrastructure changes. The intermodal planning model could be used to evaluate:

  - Changes in the geometry of the roadways such as adding/deleting one lane, adding or deleting a new roadway/interchange.

  - The location of a new P&R facility. The analyst can use the model to examine the impact one or more P&R facilities have on the roadway network and the impact on the redistribution of the demand into auto-only, transit-only, and intermodal (auto plus transit – P&R users). One of the case studies developed for this research is the evaluation of the location of P&R facilities on the I80 corridor.

- Evaluation of the impact of traveler information to travelers. In this research we present an implementation of the static model in a case study involving the impact of pre-trip information through the use of Variable Message Signs (VMS) on car users propensity to park at P&R facilities and then use transit to complete the remaining part of their trip.

- Estimation and prediction of traffic flow characteristics through integration of the DTA-based intermodal model with the traffic surveillance system of the underlying transportation network. A specific use of this capability for the P&R users is real-time estimation and prediction of the shortest path for each OD pair.

Literature Search

Impact of Traveler Information on Traveler Behavior Models

In this section five models (Models 1 to 5) are reviewed that could be used to predict the impact of pre-trip information on travelers' behavior. The extent to which travel behavior can be affected by the provision of information depends on what information is provided, when and where it is provided, and how it is provided. The higher the position in the travelers' decision making chain at which information is provided, the larger the number of decisions of travel behavior can be influenced. It is well known though that traffic forecasting is not as reliable in urban/suburban settings that experience a high variability in traffic flow characteristics that usually stem from incidents due to accidents, daily construction, weather conditions and special events. The impact of these incidents is not known to all travelers and result in unpredictable traffic conditions. This variability in traffic conditions make pre-trip planning a challenge for many travelers.

There are several papers that are trying to formulate this problem. In De Cea, Cabrera and Florian(1) presented several approaches to formulate network equilibrium models with combined modes. In that paper, a combined mode auto-metro is selected to be representative of mode combinations, for analyzing combined mode trips called intermodal trips in network equilibrium models. An intermodal trip is defined as the combined trip of at least two modes of transport such as: auto plus bus, auto plus train, bus plus train, van plus train, other. When such trips occur, there are two main modeling issues that arise:

- First, is the *modeling of the choice of the intermodal mode type*; how is the choice among pure mode trips and intermodal mode trips represented and what behavioral assumptions govern the route choice for intermodal mode trips?

- Second, is the *modeling of the choice of transfer nodes*; how is the transfer node represented and what behavioral assumptions govern the route choice from origins to transfer nodes, and from transfer nodes to destinations.

Depending on the modeling approach selected for the representation of mode, transfer node and route choices, authors have identified three types of models:

- In the first model the choice of the intermodal mode and the transfer node point is part of the network route choice model only. The main assumption is that the network is subject to congestion effects and that the Wardrop's user optimal principle governs the route choice – *under steady state conditions, for each OD pair all used paths will experience the same travel cost and all unused paths will have a cost that is either equal or higher than the used path cost*. Thus, for a specific OD pair, travelers use an intermodal mode path if its generalized path cost equals that of all the other used paths (intermodal or single mode (auto or transit)). Since it is assumed that the OD matrix is known, this problem is defined as a *fixed demand intermodal network equilibrium model*.

- In the second model the intermodal mode is modeled as a pure mode. Travelers choose between modes according to the mode function and then, once the mode is chosen, they choose routes on distinct sub-networks, corresponding to “pure” and “intermodal” modes. A Logit-based model is assumed which gives a proportion of trips taken by each mode according to the formula:

$$G_w^{k}(U_w) = \exp - (\alpha^k - \beta_1 U_w^{k}) / \sum_{k'} \exp - (\alpha^k \quad \beta_1 U_w^k) \qquad (1)$$

Where:

- Uwk is the user’s perception of the generalized cost of traveling between origin and destination by mode k that corresponds to a user optimal route choice of the network;
- {Uw} is the vector of generalized costs for all modes present; and
- αk’, β1 are parameters that are calibrated by using mode choice data.

The denominator in (1), contains the sum over all the modes available for an O-D pair *w*, which are indexed *k’*. The models in this paper assume that the intermodal mode alternative is not relevant when the transit (metro) mode is available for travel between O-D pair *w*. The choice of transfer nodes in this model is a direct consequence of the paths that are generated during the computation of the bimodal network equilibrium model and the assignment of the resulting car-transit O-D trips matrix to the corresponding combined mode paths. While this model accounts for the different perceptions the travelers make on the pure and intermodal modes in a mode choice model, the transfer node choice of the combined mode trips is modeled as part of the route mechanism. Hence, the different attributes of the transfer facilities may not be considered explicitly and this model has the limitation that the transfer choice is handled by a simplistic behavioral assumption.

- The third model is an extension of the second model that incorporates explicitly, in the demand sub-model, the transfer choice for intermodal mode trips. The number of intermodal mode trips between OD pair *w* by transfer node *t* is determined by introducing an additional Logit model G_2:

$$G_{w,t}^{k}(U_w^{c}) = \exp - (\alpha_t^{c} - \beta_2 U_{w,t}^{c}) / \sum_{t\sim} \exp - (\alpha_{t\sim}^{c} - \beta_2 U_{w,t\sim}^{c}) \qquad (2)$$

Where:

- $U_{w,t}^c$ represents the user’s perception of the generalized travel cost for combined mode *c* via transfer node *t*, assuming a user optimal route choice on the car and transit networks;
- $\{U_w^c\}$ is the vector of generalized travel cost perceptions for the combined mode via all transfer nodes *t*; and

- $\alpha_{t\sim}{}^{c}, \beta_2$ are parameters that are calibrated on the observed data, in order to adjust the model to observed behavior with respect to the choice process represented by demand model.

In Boile, Spasovic and Bladikas [(2)] a methodological framework for analyzing the effects of various policies on network flow pattern and associated travel costs in intermodal network were presented. The model produces the equilibrium flows over an intermodal network that minimizes user costs, total travel cost of each policy, rail service and parking capacity additions needed to accommodate rail ridership increase.

The approach adopted in this model, formulates the commuters' choice of auto or rail transit within the demand side of the model formulation via a binomial logit model, which splits the total demand between auto and transit. Then, within transit, the choice between pure transit (walk-to-rail) and intermodal (auto-to-rail) trips is treated as a least cost routing problem.

The above-mentioned models assume that all travelers have perfect information on the traffic conditions and they consistently make route choices based on the utility functions mentioned above. However, traffic conditions are rarely known to all travelers due to the dynamic nature of traffic and the presence of incidents whose impact is difficult to estimate and consequently extremely difficult to be estimated by the travelers. In the majority of cases a percentage of travelers will choose to change their route in real-time where another percentage will stay on the originally planned route.

Given traffic information, the travelers choose their routes based on the relevance of the information provided for their own OD trips, the reliability of the information provided, and the users' personal characteristics and preferences. In reference to the Park and Ride type of drivers, the most important information are: 1) What is the probability of finding a free parking space upon arrival at the P&R facility, 2) What is the expected waiting time for the next bus or train that services his/her final destination, 3) What is the estimate/prediction of the intermodal path travel time for his/her specific OD pair and the associated auto only and transit only estimates.

Japan and the Netherlands have adapted and tested Advanced Traveler Information Systems (ATIS). The results of these studies can be found in Krann[(3)] and Thompson[(4)], respectively. These studies have not been reviewed in detail as the user characteristics and preferences are widely different from those in the US. Their use is therefore limited in the methodology used rather that the corresponding outcomes of the studies. Mathematical and computer simulation models have been widely used in route and mode choice behavior due to the limitations in obtaining real life data.

Transportation simulation models have been used to model the travelers' behavior. Several studies such as Adler, Recker and McNally[(5)] ,Balmforth , Bonsall and Palmer[6] , Bonsall and Parry[7] , Bonsall, Firmin, Anderson and Palmer[8] , Chen and Mahmassani[9] , Koutsopoulos, Lotan andd Yang[10], Koutsopoulos, Polydoropoulou and Ben-Akiva[11] , Vaugh, Abdel-Aty, Kitamura, Jovanis, Yang, Kroll, Post and Oppy[12] have shown that transportation simulators could offer very powerful tools in analyzing travelers route choice under traveler information. Computer simulators are used to:

- Simulate real-world decision-making environments, and to record the behavior of human subjects interacting with this simulated environment;

- Aid in calibrating models of the decision-making behavior; and

- Permit simulations of decision-making behavior in a large variety of contexts.

Computer simulation models typically consist of two components [13]:

- A dynamic driver simulation model,

- A traffic simulation model.

The driver simulation model captures the drivers' behavioral, preferential and cognition characteristics' effect on their route and mode choice decisions. The capabilities of such models are based on [3]:

- The manner in which a simulator can effectively translate the real world situation to the simulation environment and,

- The manner by which physical elements of the real world that play an active role in the choice process are represented.

The output from these traveler simulation models forms the input to the traffic simulation models, which are used to estimate the assignment of the travelers on the network based on their specific OD paths. The analysts can then perform statistical analyses to produce the corresponding traffic flow characteristics (traffic flow, travel time) at the link, OD path, sub-network or network level. These models could then be used as emulators of real-time traffic conditions to evaluate the route choices of the travelers under a simulated environment.

As stated earlier, the route choice behavior depends on the information provided, as this affects the cognitive process of the driver. Thus, it is important to understand the information needs of the traveler, its accumulation and how, why and when s/he implements the information accumulated. The general approach suggests that travel is defined in three stages (see Figure 25): pre-trip planning, en-route assessment and adjustment, and post-trip evaluation. The first two stages involve direct decision making in real-time. The third stage is a longer-term evaluation of past trip-making success creating the link between past performance and future impression that shapes the traveler behavior over time.

Studies have shown that the reliability of the information presented is one of the most important factors to affect the compliancy behavior of the driver [12, 13].

Static User Equilibrium Intermodal Model Developed in this Study

In this study, we concentrated on the development of an intermodal planning model that captures the route choice characteristics of P&R users as well as auto and transit (bus or train) users. In addition, we further developed a sub-model that takes into consideration the impact of P&R messages displayed on Variable Message Signs (VMS) in choosing a P&R facility. Whereas, there is substantial literature on the impact of pre-trip and en-route information on route choice behavior, there is limited research on models that can represent P&R intermodal types of users.

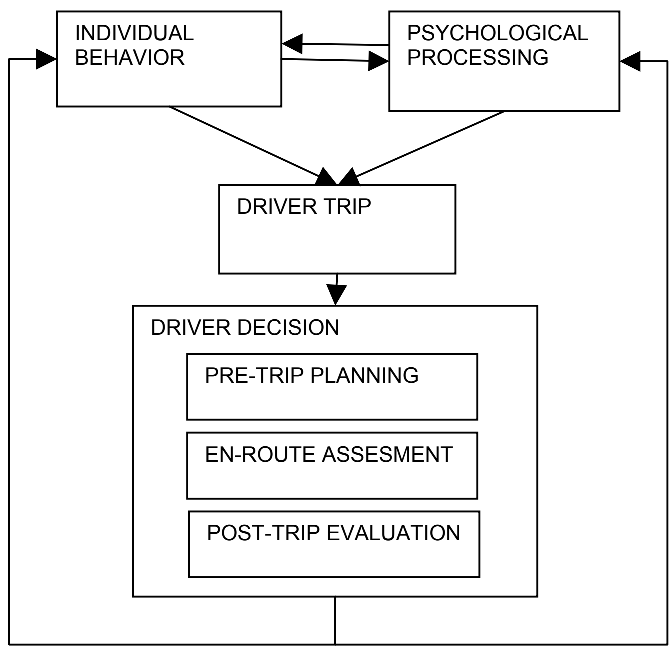

Figure 1. General schema for driver behavior model

First we present the three steps involved in assessing the impact of parking and transit information on mode choice.

Step 1. Determining the Variables that are Relevant to Mode Choice

This step includes the personal data set, and the travel characteristics that influence the driver's mode choice decision. This can be initially compiled through literature review of previous work in this area. The main data that are used to model the travelers' route and mode choice behavior are:

- Age.

- Sex.
- Income group.
- Occupation.
- Work schedule.
- Tolerance to late arrival at work.
- Preferred arrival time at work.
- More than one work location?
- Use carpool?
- Number of cars owned.
- Average travel time.

The travel characteristics of the driver that affect route and mode choice are:

- Trip purpose.
- Origin and destination.
- Receive traffic information?
- Response to recurring congestion.
- Expected delay on usual routes [3].
- Travel time on alternate routes [3].
- Perceived congestion level on alternate routes [3].
- Information sources [3].
- Reliability of information obtained.

Step 2. Data Collection Methodologies used in travelers' route and mode choice models

The main methodologies used to obtain information for route choice models are:

- Stated preference survey.
- Revealed preference survey.

- Computer simulation models.

Surveys of stated preference and revealed preference towards congestion and ATIS have a response rate of 40% to 60% in the US.

Step 3. Route and Mode Choice Model Development

Once the data is collected, a model can be developed to represent the real life decision process in choosing mode and route for a specific OD pair. Then, the effect of the variables considered in the model on choice can be analyzed. The following section presents examples of different theories employed to model route and mode choice.

<u>Modeling the impact of pre-trip information on drivers' behavior in Route-Choice.</u>

Model 1

In the study of Khattak, Polydoropoulou and Ben-Akiva [(16)], the goal was to explore how travelers react to unexpected congestion and how they might respond to ATIS. Travelers' departure times, routes and mode choice selections were examined through a survey in Bay Area auto commuters. The impact of various factors such as sources of information, trip characteristics and route attributes on travelers' response to unexpected congestions were investigated. Stated preference approach was used to determine the effect of future ATIS technologies to pre-trip response. The multinomial logit model was used to develop a combined stated preference and revealed preference model.

Based on earlier work, Ben-Akiva, Kayasi, Polydoropoulou [(17)], Khattak, Schofer, Koppelman [(18)], Ben-Akiva, Bolduc [(19)] and Schofer, Khattak, Koppelman [(20)], an ATIS behavioral framework can be summarized as follows: In urban transportation systems incident bottlenecks are prevalent. Through electronic sources or direct observation travelers receive information and in the light of their knowledge they interpret the information. This interpretation translates into a perception of travel time and delay. Perceptions, restrictions and individual characteristics create a preference for certain modes, routes and departure times. This preference is also subject to previously acquired knowledge and on thresholds of the main parameters. Observable alternatives that have outcomes are results of these preferences. If those outcomes are satisfying, they will probably be repeated, creating a commuter pattern.

Various aspects of travel information influence travelers' decisions. Processing of information depends on its content, presentation style, whether it is static, dynamic or predictive and whether is qualitative or quantatitive. The perception of delay and the quality of information is especially important under incident related congestion. Many aspects of event-related information impact travelers' decisions. When travelers approach or reach their expectation tresholds, the travelers' decisions are reviewed. Travelers have a set of restrictions that partly influence their patterns. For example, this restriction could be arrival to work before start time and any diversion from the preffered arrival time will probably be onerous.

In the study conducted by mail back questionnaires were distributed to peak-hour commuters crossing the Golden Gate Bridge, San Fransisco [35]. The questionnaire contained questions regarding normal travel patterns, pre-trip response, willlingness to change travel patterns and personal information. Travelers were asked to recall the time when they became aware of unexpected congestion and whether they modified their travel patterns. This study specifically concentrated on travelers who became aware of unexpected congestion on their home to work trip.

The uniqueness of this study is the estimation of the ATIS response model that combines data from two sources: revealed preference (RP) and stated preference (SP) data.

The utility maximized by each traveler in RP context is defined by:

$$U_{RP} = V_{RP} + \varepsilon \tag{3}$$

- V_{RP} is the systematic utility function influencing RP decisions
- ε is the random utility component influencing RP decisions

The utility maximized by each traveler in SP context is defined by:

$$U_{SP} = V_{SP} + \nu \tag{4}$$

- V_{RP} is the systematic utility function influencing SP decisions
- ε is the random utility component influencing SP decisions

It is assumed that the non-measured components of the RP utility (ε) and the SP utilities (γ) are independently and identically Gumbell distributed, and the level of noise in the data sources is represented by the variance of ε and v. We define μ^2 to be the ratio of the variances:

$$u^2 = \mathrm{var}(\varepsilon) / \mathrm{var}(\nu) \tag{5}$$

and therefore the SP utilities can be scaled by μ

$$\mu U_{SP} = \mu V_{SP} + \mu\nu, \tag{6}$$

such that the random variable (μ γ) has a variance equal to that in the RP utility (ε). It is possible to use both RP and SP observations in a logit estimation procedure that requires equal variance across observations. However the SP utilities are scaled by an unknown constant μ, which needs to be estimated.

Thus, systematic utilities were defined as follows:

$$V_{RP} = \alpha' w + \beta' x + \delta' c \tag{7}$$

$$\mu_i \, V_{SPi} = (\alpha_i' w \; + \beta' x + \gamma' z) \, \mu_i \tag{8}$$

Where:

- *"i"* denotes the specific ATIS scenario.
- Vector ***w*** represents dummy variable for the alternative constants of each model.
- All relative coefficients *(α, α_i)* are unconstrained.

The SP constants capture the influence of each ATIS scenario on travellers' decisions. Therefore the comparison of the RP and the SP constants gives the pre-tripe switching propensity due to information provided by ATIS. Sharing *β* in both RP and SP models implies that trade-offs among the attributes included in **x** are the same in both actual travel behaviour and the SP behaviour. In the model the **x** vectors represent all travel-related coefficients, such as travel time, expected delay, the congestion level on alternate route and scheduled delay variables. Vectors ***c*** are specific to the RP model and include information source variables used in the RP context. Factors inherent in SPs are represented by **z** with the corresponding coefficients *γ*. In this case a variable representing the actual choice included in **z** may capture the effect of justification bias. In the combined model the coefficients *γ* are restricted to be the same among the five SP models, assuming the same marginal contribution of **z** to the SP utilities. The joint estimation of RP and SP data is conducted by using the tree logit methodology. The construction of the artificial tree and the required steps for the model estimation are described by Bradley and Daly [21].

The RP portion of the model describes travellers' decisions when they become aware of unexpected congestion along the route. The following alternatives were used in the estimation:

1. Did not change normal travel pattern.

2. Change Route (CR).

3. Left Earlier (LE) from the origin.

4. Left later (LL) from the origin.

5. Used public transportation (PBL).

6. Left earlier and changed route (LE and CR).

7. Canceled trip (CANCEL).

Seven major categories of variables were included in the model: a) travel time, b) expected delay, c) schedule delay, d) usual bottleneck delay, e) congestion on alternative route, f) knowledge of travel time and g) information sources.

Travel time is included as a generic variable. Travel time in each alternative was used as follows:

1. Do not change alternative; the reported usual travel time was used for estimation.

2. Change to alternative route; the reported travel time on the alternative route was used, and 0 was used if the travel time was not reported.

3. Leave earlier alternative; the reported travel time was used if the person left work 30 min earlier, and 0 was used if the travel time was not known.

4. Leave later alternative; the minimum of the usual travel time and the time for the leave earlier alternative was used.

5. Public transportation alternative; the transit travel time was used if it was reported, and 0 was used otherwise.

6. Leave earlier and change to alternative route; the minimum of travel time between the leave earlier option and change to alternative route option, if those were reported, was used, and 0 was used otherwise. It is assumed that this joint decision is the outcome of a trade off between the two options under consideration.

7. Cancel trip alternative. For the cancel trip alternative the travel time is 0.

Expected delay on the usual route is included as an alternative specific variable on the do not change alternative. The natural logarithm of the expected delay minus 2 min was used in the estimations. By using the logarithm it was assumed that travelers have a reduced sensitivity to increasing delays, because the minimum reported delay was 3 min, so the assumption is that delay of 2 min or less will not cause any traveler to change his/her travel pattern.

Scheduled delays, early and late, were calculated for travelers with a required work start time. The notation for the variables is:

- t_d= departure time.
- t_a= arrival time.

- t^*= desired arrival time.
- Δ=reported flexibility in arrival time.

Then:

- Late schedule delay (LSD), $t_a > t^*$

$$LSD = \max [0, t_a - t^* - \Delta]. \quad (9)$$

- Early scheduled delay (ESD), $t_a < t^*$

$$ESD = \max [0, t^* - t_a]. \quad (10)$$

Usual Bottleneck Delays is a usual dummy variable that takes the value of 1 if travelers have a usual bottleneck and 0 otherwise. This delay is most likely to occur on the Golden Gate Bridge toll plaza.

Congestion on Alternative Route is a dummy variable that takes the value of 0 if it is not congested and 1 if it is usually congested or heavily congested. The congestion on alternative route was included in the change route and the change departure time and change route alternatives.

The effect of knowledge of travel times on behavior and the effect of experience on behavior was captured by creating five alternative specific dummy variables for the alternatives that had observations with non-reported travel times.

Information sources that the travelers used were: Electronic sources (TV, radio, computer, phone); Non-electronic sources (word of mouth, direct observation); Both electronic and non-electronic sources. A dummy variable was created for the acquisition of information from electronic and both electronic and non-electronic sources and these were included in the no-change alternative, leaving the non-electronic sources as the base case.

The SP portion of the model examines commuter responses to ATIS. For each ATIS a multinomial logit model was developed, with the following alternatives:

- Cannot say. It is assumed that these travelers would not change their travel patterns (do not change).
- Change route (CR).
- Leave earlier (LR).
- Leave later (LL).
- Take public transportation (PBL).

The cancel trip was not included in the model specification because of few observations of this alternative. The main differences between models and the RP model are the absence of other information sources (fixed as ATIS in this case) and the presence of experience or justification variables. These are alternative specific dummy variables taking the value of 1 if the alternative was chosen under the RP model and 0 otherwise. To capture the potential biases introduced by the experienced delay, a dummy variable equal to 1 if the actual delay experienced was higher then the initially expected delay reported in the RP situation was included in the departure time alternatives. Table 18 presents the results of a combined RP and SP model. All scale coefficients are significantly different from zero. Separate RP and SP models were also estimated and it was found that the combined model had a better fit than the separate models.

Table 1. Results of Combined RP and SP Model

Variables		Coefficients	t-statistics
Current info-	Constant 1 (CR)	-1.47	-3.9
	Constant 2 (LE)	-1.82	-4.9
	Constant 3 (LL)	-2.51	-6.5
	Constant 4 (PBL)	-3.66	-7.7
	Constant 5 (LE&CR)	-2.54	-6.1
	Constant 6 (CANCEL)	-5.25	-9.2
Qualitative info	Constant 1 (CR)	-1.24	-3.2
	Constant 2 (LE)	-0.66	-2.2
	Constant 3 (LL)	-1.98	-4.1
	Constant 4 (PBL)	-1.74	-3.6
Quantitative	Constant 1 (CR)	-0.63	-1.8
	Constant 2 (LE)	0.04	0.1
	Constant 3 (LL)	-0.71	-2.1
	Constant 4 (PBL)	-1.32	-2.9
Predictive-	Constant 1 (CR)	-0.49	-1.4
	Constant 2 (LE)	0.24	0.7
	Constant 3 (LL)	-0.69	-0.2
	Constant 4 (PBL)	-1.33	-2.9
Prescriptive Route-	Constant 1 (CR)	0.98	2.4
	Constant 2 (LE)	-0.88	-2.4
	Constant 3 (LL)	-2.75	-4.1
	Constant 4 (PBL)	-2.27	-3.6
Prescriptive Mode-	Constant 1 (CR)	-0.56	-1.6
	Constant 2 (LE)	-0.86	-2.4
	Constant 3 (LL)	-2.36	-4.0
	Constant 4 (PBL)	-0.10	-0.3
Travel Time		-6.47	-3.7
Log (Exp. Delay-2 min) (Do not change)		-0.19	-2.4
Late Schedule Delay (x10hrs)		-4.35	-1.5
Early Schedule Delay (x10hrs)		-0.50	-1.9
Usual Bottleneck Dummy (CR)		0.28	1.1
Usual Bottleneck Dummy (LE)		-0.16	-0.7
Usual Bottleneck Dummy (LL)		-1.46	-2.8
Usual Bottleneck Dummy (PBL)		0.66	2.0
Usual Bottleneck Dummy (LE&CR)		1.05	2.1
Congestion level (CR)		-0.23	-1.5
Travel Time Dummy (CR)		-1.62	-4.7
Travel Time Dummy (LE)		-0.39	-1.4
Travel Time Dummy (PBL)		-2.84	-4.3
Travel Time Dummy (LE&CR)		-2.10	-4.0
Info Both Dummy (Do not change)		-3.76	-4.9
Info electr. Dummy (Do not change)		-2.19	-4.1
Dummy Act>Exp. Del. (LE)		0.28	2.2
Dummy Act>Exp. Del. (LL)		0.37	2.1

Variables	Coefficients	t-statistics
Justification (Do not change)	-0.18	-1.2
Justification CR (CR)	1.62	4.4
Justification CR AND LE (CR)	1.38	3.1
Justification LE (LE)	1.33	4.4
Justification CR AND LE (LE)	1.01	2.8
Justification LL (LL)	2.38	4.5
Justification PBL (PBL)	3.92	4.4
(SP1-Qualitative Info)	1.10	4.6
(SP2-Quantitative Info)	1.05	4.6
(SP3-Predictive Info)	0.87	4.6
(SP4-Prescriptive Route)	0.68	4.5
(SP5-Prescriptice Mode)	0.74	4.5
Log likelihood (initial)	-4498.89	
Log likelihood (convergence)	-3677.57	
Number of observation	2703.00	
ρ^2	0.24	

Model 2

In the paper of Polak and Jones[22] the effect of pre-trip information on travel behaviour was described. The purpose of this study was to investigate travelers' requirements for different types of traveler information and methods of enquiry and to relate the process of information aquisition to changes in travel time. The research was done utilizing stated preference approach, based on a computer simulation of an in-home pre-trip information system offering information on travel times from home to City center, by bus and by car, at different time periods of the day. A novel feature of the stated preference excercise was that respondents efficiently generated their own choice set of alternatives through the process of information aquisition. The surveys were undertaken parallel in Athens, Greece and Birmingham, United Kingdom[22].

The essential idea was to develop a computer-based interview procedure that presented a credible simulation of an in-home pre-trip information system. Respondents were allowed to make enquiries of the system and, after they were satisfied they had aquired sufficient information, they would be required to rank the 'enquired-about' alternatives in order of preference. The final version of the simulation had the following capabilities:

- It provided information on expected network travel times by bus and car at different time of the day.
- In the case of car, information was also provided on expected parking search times in the city.

- A rudimentary public transport time-table was included, to enable the system to present information concerning expected arrival times of buses at stops.

- Respondents were able to enquire about either the expected travel conditions associated with the particular departure time or given these travel conditions, at what time they must depart in order to arrive at their destination in the city by a certain deadline.

Interviewing for the main survey was carried out at selected locations in Birmingham and Athens. A set of screening criteria were used in order to recruit only those people likely to have greatest propensity to use and be affected by pre-trip information. A system of quota controls on various personal and journey related factors were also used to ensure that the final sample contained an adequate representation of potentially significant segments of population.

There are significant differences in the travel characteristics of the respondents from the two cities that relate to differences in social and institutional arrangements in Athens and Birmingham, respectively.

In Athens 66% of commuters have access to free parking versus 59% in Birmingham.

Another significant difference between the two cities is the flexibility that travelers have in the timing of their journey. The significantly greater flexibility in journey timing displayed by the Birmingham sample probably reflects the higher penetration of flexible working-hours arrangements in Birmingham and greater restrictions in shop and public facility opening in Athens.

A further significant difference between the two cities concerns the extent to which the travelers' existing journey patterns reflect the adaptation to congested conditions. In Birmingham almost one quarter stated that they had actively retimed their current car journey to avoid congestion. The re-timing that occurred involved shifts to, both earlier and later with respect to their ideal departure times. In Athens, only 8% of journeys had been re-timed and all had involved a shift to an earlier departure time. The average magnitude of the earlier shift was also significantly less then in Birmingham.

Respondents in Athens appeared to be more interested than their counterpart in Birmingham in making enquires concerning public transport options, which has important implications for the effectiveness of such system as demand management tools. In order to explore possible explanations for this finding, a logit model was estimated predicting the probability of a respondent enquiring about public transport option on Day 2, as a function of personal and journey related factors. The estimation results are summarized in Table 19, where a positive coefficient value indicates that the corresponding variable increases the probability of a public enquiry being made. The estimation results confirm the existence of a significant national difference in propensity to make bus-oriented enquires. The results showed that travelers in Athens showed greater interest in bus services. Further, the results indicated that the probability of enquiring about buses decreases with increasing trip distance, maybe reflecting a perception by the travelers that bus is less competitive on longer distances.

The modal and timing characteristics of the first ranked alternatives on day 2 suggest that there may be significant differences of the impact of pre-trip information systems in the two cities. In Birmingham, those engaged on work trips appear most reluctant to contemplate switching mode but quite willing to consider significant re-timings of their trip. By contrast, those engaged in work trips in Athens present just the opposite tendency, with just a slight interest in re-timing and much greater willingness to use public transportation.

The data from the ranking exercise also enabled the exploration of travelers' underlying preferences. Table 20 presents a series of multinomial logit models developed by expanding the preference data into choice data.

Table 2. Estimation results of the survey in Athens, GR and Birmingham, UK

Variable		Coefficient	(t-statistic)
Country			
	Greece	2.012	(7.21)*
	UK	-	
Gender			
	male	-0.088	(-0.35)
	female	-	
Age			
	16-24	0.015	-0.01
	25-44	-0.567	(-0.73)
	45-64	-0.725	(-0.92)
	>64	-	
Socioeconomic group			
	Professional/managerial	-0.31	(-0.74)
	Supervisory/administrative	0.17	(0.43)
	Skilled manual	0.203	(0.55)
	Semi/n-skilled manual and other	-	
Purpose			
	Work/education	0.211	(0.73)
	Other	-	
Frequency of journey to city center			
	>once per week	0.043	(0.12)
	<=once per week	-	
Free parking in the city center			
	Yes	-0.674	(-2.15)*
	No	-	
Journey re-time to avoid congestion?			
	Yes	0.125	(0.43)
	No	-	
Current travel time by car		-0.247	(22.45)*
Current parking search time		-0.019	(0.74)
Constant(enquire about bus)		1.423	(1.499)
Diagnostics			
	N	628	
	L(0)	435.29	
	L(convergence)	267.73	
	Rho-squared	0.384	

Table 3. Results of ranking-based preference modeling

Variable	**Coefficient (and t-statistic)**							
	Birmingham work		**Birmingham non-work**		**Athens work**		**Athens non-work**	
Later shift in departure time	-0.009	(-2.5)	-0.004	(-2.0)	-0.068	(-3.7)	-0.001	(-0.1)
Earlier shift in departure time	-0.017	(-2.3)	-0.001	(-0.4)	-0.006	(-0.9)	-0.012	(-0.8)
Travel time	-0.105	(-4.3)	-0.089	(-5.9)	-0.120	(-6.0)	-0.139	(-5.0)
Parking search time	-0.026	(-0.7)	-0.069	(-3.5)	-0.029	(-1.2)	-0.159	(-3.9)
Egress time	-0.099	(-1.0)	-0.037	(-0.9)	-0.016	(-0.4)	-0.101	(-1.2)
Bus dummy	-1.748	(-3.2)	-1.233	(-4.1)	-0.308	(-0.8)	-2.090	(-4.0)
Enquiry order (1=first etc.)	-0.467	(-2.9)	-0.490	(-3.5)	-0.259	(-2.8)	-0.144	(-1.1)
Diagnostics								
N	111		156		173		84	
L(0)	-110.1		-164.9		-218.2		-106.4	
L(convergence)	-72.4		-108.6		-163.9		-78.1	
Rho-squared	0.342		0.341		0.348		0.266	

Several interesting observations can be made on these models. In all the models the variable corresponding to the enquiry order of the options has a negative coefficient and, with the exeption of a small Athens non-work segment, it is statisticaly significant. This provides evidence that the process of information acquisition is structured according to travel preferences with travelers tending to enquire first about their more prefered options and then only subsequently less prefered alternatives.

Model 3

A joint model for route choice and departure time decisions with and without pre-trip information is formulated, based on the extensive home-interview of commuters in Taiwan, Jou[23]. The model specifications for both systematic and random components are formulated. A probit model is used for the joint model, allowing the introduction of state dependence and correlation in model specification.

How a pre-trip information impacts commuters' decision-making is shown in Figure 26, These characteristics, shown in the figure, and whether a commuter receives a pre-trip information together form a commuter's decision making mechanism, deciding to accept or decline his departure travel time and route choice. S_{id} is indicator variable for departure time (d) switch for traveler *i* and S_{ir} is indicator variable for route (r) switch for traveler *i*. If the departure time/route switch has happened the value of corresponding variable is 1 and 0 otherwise. So, all possible combinations for commuter *i* are (0,0), (1,0), (0,1), (1,1).

A latent variable, internal to each traveler, in this study is part of mechanism underlying the switching and cannot be measured nor observed directly. Commuter switch their departure time and route as long as their latent variable is greater then threshold, which is set to 0 in this study. The functional structure is derived after observing actual commuters' decision to switch or not to switch departure times or routes in response to exogenous information and expected traffic conditions.

Two scenarios are being investigated, with and without pre-trip information. Instead performing estimations for these two variables and comparing them, a joint latent variable containing both scenarios has been introduced and derived for simplifying estimation. Because of the assumption of normal distributed error term in latent variable, probit framework has been introduced, because of its more flexible model specification through parameters in variance-covariance matrix. Both scenarios, with and without pre-trip information, are introduced to theoretically model commuters' choices and a joint model incorporating these two scenarios has been derived. The terms incorporated in the expressions are listed in Table 21, and the parameters and definitions of variance-covariance matrix latent variable are explained in Table 22.

Table 4. Definitions of latent variable elements

Element		**Definition**
I		With pre-trip information
N		Without pre-trip information
f (●)		Systematic component of departure time
h (●)		Systematic component of route
$\mathbf{X_i}$		Socioeconomic characteristics for commuter *i*
$\mathbf{Z_{id}}$		Attribute vectors of departure time for commuters *i*
$\mathbf{Z_{ir}}$		Attribute vectors of route for commuters *i*
$\mathbf{\Theta_{id}}$ **and** $\mathbf{\Theta_{ir}}$		Parameters to be estimated
$\boldsymbol{\varepsilon_{id}}$		Error term of departure time for commuter *i*
$\boldsymbol{\tau_{ir}}$		Error term of route for commuter *i*
$\mathbf{w_i}$		A binary indicator variable; =1, if with pre-trip information; 0 otherwise

Table 5. Parameters and definitions of variance-covariance matrix in latent variables

Parameter		**Definitions**
$\boldsymbol{\sigma_1^2}$		Variance of departure time latent variable with pre-trip information
$\boldsymbol{\sigma_2^2}$		Variance of route latent variable with pre-trip information
$\boldsymbol{\sigma_3^2}$		Variance of departure time latent variable without pre-trip information
$\boldsymbol{\sigma_4^2}$		Variance of route latent variable without pre-trip information
$\boldsymbol{\gamma_1}$		Covariance of departure time and route latent variables with pre-trip information
$\boldsymbol{\gamma_2}$		Covariance of departure time and route latent variables without pre-trip information

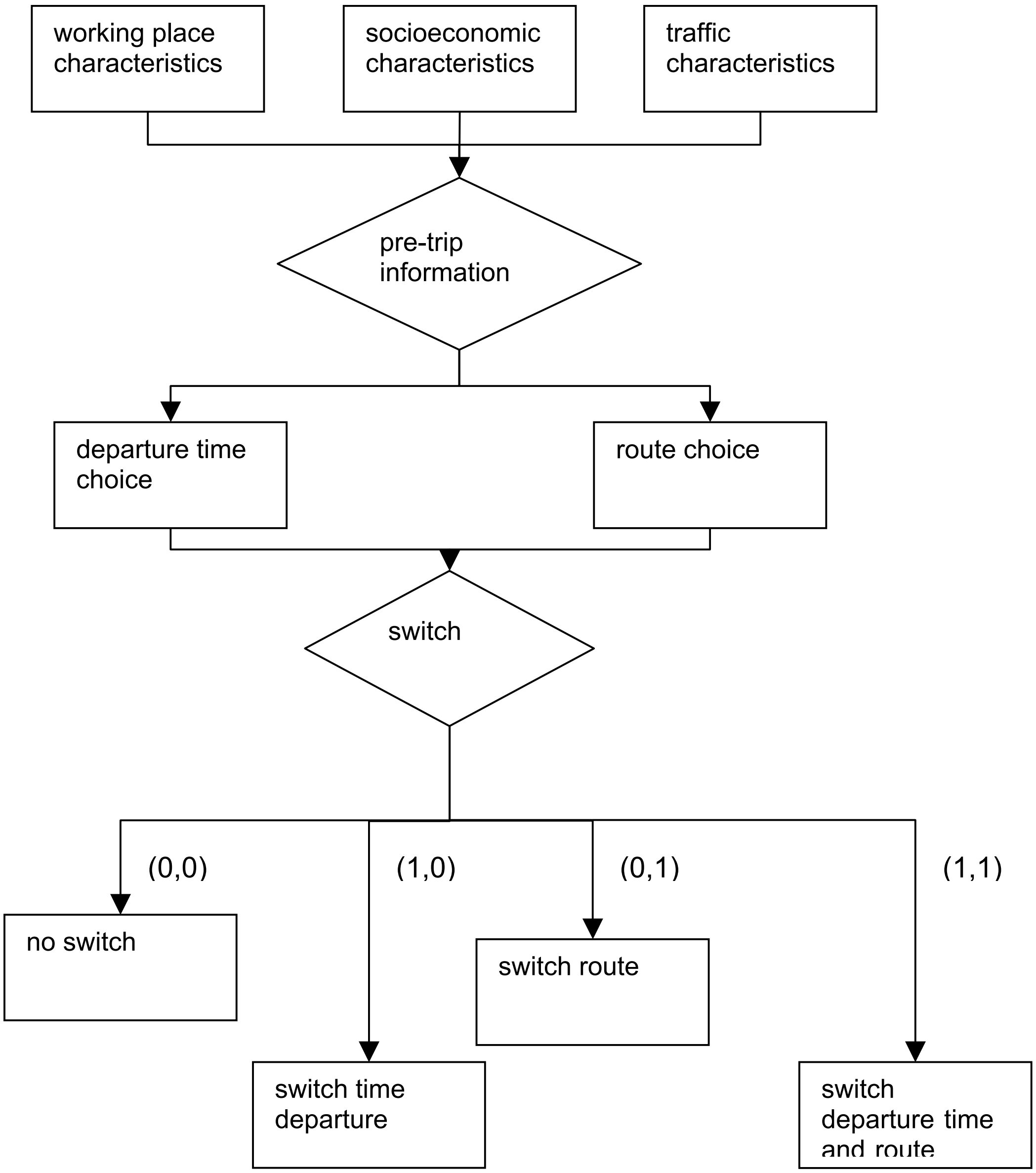

Figure 2. Impact of pre-trip information on commuters' decision-making

The following expressions are separate models for the two scenarios:

$$Y^{T}{}_{id} = f^{T}(X_{T}, Z_{id}, \Theta_{id}) + \varepsilon^{T}{}_{id} \tag{11}$$

$$Y^{T}{}_{ir} = f^{T}(X^{T}, Z_{ir}, \Theta_{ir}) + \tau^{T}{}_{ir} \tag{12}$$

Where T =I in scenarios with pre-trip information, and T=N in scenarios without pre-trip information. The random terms εIid and $\tau^{I}{}_{ir}$ are also assumed to be multivariate with zero means and general covariance can be expressed as:

$$\Sigma^{I} = \begin{bmatrix} \sigma_1^2 & \gamma_1 \\ \gamma_1 & \sigma_2^2 \end{bmatrix} \tag{13}$$

Where:

- γ_1 is the covariance of departure time and route with pre-trip information. It assumes contemporaneous correlation between departure time and route choice for a certain commuter, reflecting dependence on the same set of experienced traffic conditions.
- σ_1^2 and σ_2^2 are the corresponding variances of departure time and route latent variables, respectively, with pre-trip information.

Similarly,

$$\Sigma^{N} = \begin{bmatrix} \sigma_3^2 & \gamma_2 \\ \gamma_2 & \sigma_4^2 \end{bmatrix} \tag{14}$$

Where:

- **Error! Objects cannot be created from editing field codes.** is the covariance of departure time and route with pre-trip information. It assumes contemporaneous correlation between the departure time and route choice for a certain commuter, reflecting dependence on the same set of experienced traffic conditions.
- **Error! Objects cannot be created from editing field codes.** and **Error! Objects cannot be created from editing field codes.** are the variances of departure time and route latent variables, respectively, with pre-trip information.

Latent variables for a joint model, with and without pre-trip information, of a departure time and route for a commuter with or without pre-trip information can further be developed as:

$$Y_{id} = w_i Y_{id}^{I} + (1 - w_i) Y_{id}^{N} \tag{15}$$

$$Y_{id} = w_i Y_{ir}^{I} + (1 - w_i) Y_{ir}^{N} \tag{16}$$

Y_{id} can be derived as:

$$Y_{id} = w_i\left[f^I(X_i, Z_{id}, \Theta_{id}) + \varepsilon_{id}^I\right] + (1 - w_i)\left[f^N(X_i, Z_{id}, \Theta_{id}) + \varepsilon_{id}^N\right]$$

(17)

$$= w_i f^I(X_i, Z_{id}, \Theta_{id}) + (1 - w_i) f^N(X_i, Z_{id}, \Theta_{id}) + (1 - w_i)\varepsilon_{id}^N + w_i \varepsilon_{id}^I$$

Where:

- w_i is an indicator variable that has a value of 1 when there is a pre-trip information, and a value 0 for scenarios without pre-trip information.

And

$$\varepsilon_{id} = w_i \varepsilon_{id}^I + (1 - w_i)\varepsilon_{id}^N \quad (18)$$

$$f(X_i, Z_{id}, \Theta_{id}) = w_i f^i(X_i, Z_{id}, \Theta_{id}) + (1 - w_i) f^N(X_i, Z_{id}, \Theta_{id}) \quad (19)$$

Further:

$$Y_{id} = f(X_i, Z_{id}, \Theta_{id}) + \varepsilon_{id}$$

(21)

$$Y_{id} = h(X_i, Z_{id}, \Theta_{id}) + \tau_{id}$$

Also Σ (joint) can be derived as follows:

$$\Sigma = \begin{bmatrix} \sigma_D^2 & \gamma_{DR} \\ \gamma_{DR} & \sigma_R^2 \end{bmatrix} \quad (22)$$

Where,

$$\sigma_D^2 = w_i \sigma_1^2 + (1 - w_i)\sigma_3^2 \quad (23)$$

$$\sigma_R^2 = w_i \sigma_2^2 + (1 - w_i)\sigma_4^2 \quad (24)$$

$$\gamma_{DR} = w_i \gamma_1 + (1 - w_i)\gamma_2 \quad (25)$$

Since we can assume that the probability distribution of S_{id} is related to probability density of Y_{id} by Pr (S_{id}=1) = Pr (Y_{id}>0) and we can assume that the probability distribution of S_{ir} is related to probability density of Y_{ir} by Pr (S_{ir}=1) = Pr (Y_{ir}>0), the sample strata for the choice of commuter *i* (S_{id}, S_{ir}) can be defined as follows:

1. S_1: S_{id} =1 S_{ir}=1

2. S_2: S_{id} =1 S_{ir}=0

3. S_3: S_{id} =0 S_{ir}=1

4. S_4: S_{id} =0 S_{ir}=0

The likelihood of the whole could be formulated as follows:

$$L = \left[\prod_{S_1} \int_{-f(.)}^{\infty} \int_{-h(.)}^{\infty} W(\varepsilon,\tau) d\varepsilon d\tau\right]\left[\prod_{S_2} \int_{-f(.)}^{\infty} \int_{-\infty}^{-h(.)} W(\varepsilon,\tau) d\varepsilon d\tau\right]$$
$$\times\left[\prod_{S_3} \int_{-f(.)}^{\infty} \int_{-h(.)}^{\infty} W(\varepsilon,\tau) d\varepsilon d\tau\right]\left[\prod_{S_4} \int_{-f(.)}^{\infty} \int_{-\infty}^{-h(.)} W(\varepsilon,\tau) d\varepsilon d\tau\right] \tag{26}$$

Where W is the bivariate normal density function and can be written as:

$$W = (2\Pi|\Sigma|)^{-1} \exp\left[-\frac{(x\Sigma^{-1}x^T)}{2}\right] \tag{27}$$

Where Σ is defined above and x= (ε^T_{id}, τ^T_{ir}).

To test model's presented heterogeneity, Abdel-Aty's procedures are applied. The likelihood function looks as:

$$L = \int_{-\infty}^{\infty} \left[\prod_{S_1} \int_{-f(.)}^{\infty} \int_{-h(.)}^{\infty} W(\varepsilon,\tau) d\varepsilon d\tau\right]\left[\prod_{S_2} \int_{-f(.)}^{\infty} \int_{-\infty}^{-h(.)} W(\varepsilon,\tau) d\varepsilon d\tau\right]$$
$$\times\left[\prod_{S_3} \int_{-f(.)}^{\infty} \int_{-h(.)}^{\infty} W(\varepsilon,\tau) d\varepsilon d\tau\right]\left[\prod_{S_4} \int_{-f(.)}^{\infty} \int_{-\infty}^{-h(.)} W(\varepsilon,\tau) d\varepsilon d\tau\right] f(v_i) d(v_i) \tag{28}$$

Model specification

The latent variable is assumed to include the following components: initial, commuter characteristics, dynamic and myopic component. The short-term dynamic component is captured by myopic component, and dynamic component includes long-term dynamic effect.

The detailed departure time model specification is:

$$f(X_i, Z_{id}, \Theta_{id}) = w_i f^i(X_i, Z_{id}, \Theta_{id}) + (1 - w_i) f^N(X_i, Z_{id}, \Theta_{id}) \tag{29}$$

$$= w_i(\alpha_0 + \alpha_1 AGE_i + \alpha_2 GENDER_i + \alpha_3 NFAIL_{id} + \alpha_4 SD_i)$$
$$+ (1 - w_i)(\alpha_5 + \alpha_6 AGE_i + \alpha_7 GENDER_i + \alpha_8 NFAIL_{id} + \alpha_9 SD_i).$$

And the detailed route model specification is:

$$h(X_i, Z_{ir}, \Theta_{ir}) = w_i h^i(X_i, Z_{ir}, \Theta_{ir}) + (1 - w_i) h^N(X_i, Z_{ir}, \Theta_{ir})$$

$$= w_i(\beta_0 + \beta_1 AGE_i + \beta_2 GENDER_i + \beta_3 NFAIL_{ir} + \beta_4 SD_i)$$
$$+ (1 - w_i)(\beta_5 + \beta_6 AGE_i + \beta_7 GENDER_i + \beta_8 NFAIL_{ir} + \beta_9 SD_i).$$

Table 6. Model Parameters Specification

AGE_i		Age of commuter i: 1 if age<18; 2 if 18<=age<=30; 3 if 31<=age<=40; 4 if 41<=age<=60; 5 if age >61
$GENDER_i$		Gender of commuter i: =1 if male; =0 otherwise
$NFAIL_{id}$		Number of unaccetable arrivals (number of departure time changes) for commuter i in the most recent week
$NFAIL_{ir}$		Number of unaccetable arrivals (number of route changes) for commuter i in the most recent week
SD_i		Average absolute scheduled delay of commuter i in the most recent week: =abs(actual arrival time- work start time

Several assumptions have been made in conjunctions with the model above (Table 23). First, initial components exist for both departure time and route choice, this initial band is asymmetric for commuter with pre-trip information vs. without pre-trip information. Second, the age and gender may effect, with younger commuter more likely to switch then older, and with male more likely to switch then female. Also, the latent variable may increase in response to more switches over a period of time, reflecting the relaxation of aspiration levels due to uncertainty of experienced traffic conditions. Further, variable SD is defined as a difference between actual arrival time and work starting time in absolute values. This variable reflects inherent preferences and risk attitudes of each commuter and the characteristics of the working place.

It is important to note that the dependant variable in switching models is not an actual decision to switch for a particular commuter, but rather a response to a survey whether he/she switches departure time or route. A commuter is considered as a departure time switching whether he/she changes his departure time more then 3 times in 5 weekdays for more then 10 minutes. A commuter is considered route switching whenever he/she chooses route different from a day before. A commuter is considering receiving pre-trip information if he/she reads (or hears) traffic report before leaving home.

Table 7. Estimation results for the joint model

Component	Attributes/parameter	Estimates	t
DT initial (I)	α_0(I)	-3.91	-10.21
DT initial (N)	α_5(N)	-4.49	-5.36
DT Socio-economic 1 (I)	AGE(I)/ α_1	-1.30	-2.05
DT Socio-economic 1 (N)	AGE(N)/ α_6	-2.50	-6.36
DT Socio-economic 2 (I)	GENDER(I)/ α_2	1.75	6.02
DT Socio-economic 2 (N)	GENDER(N)/ α_7	1.28	3.92
DT Dynamic (I)	NFAIL(I)/ α_3	-1.52	-2.69
DT Dynamic (N)	NFAIL(N)/ α_8	-2.75	-4.63
DT Myopic (I)	SD(I)/ α_4	1.45	8.06
DT Myopic (N)	SD(I)/ α_9	0.81	6.45
R initial (I)	β_0(I)	-11.31	-3.45
R initial (N)	B_5(N)	-13.50	-3.62
R Socio-economic 1 (I)	AGE(I)/ β_1(I)	-5.78	-5.78
R Socio-economic 1 (N)	AGE(N)/ β_6(I)	-6.95	-4.9
R Socio-economic 2 (I)	GENDER(I)/ β_2(I)	1.15	3.03
R Socio-economic 2 (N)	GENDER(N)/ β_7(I)	0.75	2.19
R Dynamic (I)	NFAIL(I)/ β_3(I)	-3.78	-3.64
R Dynamic (N)	NFAIL(N)/ β_8(I)	-4.05	-5.12
R Myopic (I)	SD(I)/ β_4(I)	0.89	3.08
R Myopic (N)	SD(I)/ β_9(I)	0.30	9.3
DT standard deviation (I)	σ_1	15.12	4.6
DT standard deviation (N)	σ_2	12.32	5.97
R standard deviation (I)	σ_3	14.98	2.98
R standard deviation (N)	σ_4	10.56	3.45
Covariance for the con-temporaneus correlation of R and DT (I)	γ_1	5.99	5.21
Covariance for the con-temporaneus correlation of R and DT (N)	γ_2	5.10	3.45
Standard devaiation of v	σ_v	2.48	5.92
Log-likelihood convergence		-535.82	
Log-likelihood at zero		-930.21	
Likelihood ratio index		0.42	

Table 8. Log-likelihood ratio test for pre-trip information effects on departure time and route (separately and jointly)

Restricted on	L(U)	L(R)	Test statistics		Significant
DT w/o pre-trip information	-535.82	-554.12	36.60		Yes
R w/o pre-trip information		-555.32	39.00		Yes
DT and R w pre-trip information		-551.79	31.94		Yes
DT and R o pre-trip information		-560.12	48.60		Yes

The estimation results are presented in Table 24. The log-likelihood at convergence for the joint model system is –535.82. The log-likelihood when all parameters are zero is –930.21. The log-likelihood ratio clearly rejects null hypothesis that variable parameters and error correlations are zero. An informal goodness-of-fit ratio, ρ2 is on the high side at 0.42, indicating a good explanatory value of the model.

The results of log-likelihood ratio test for pre-trip information effects on departure time and route, separately and jointly, are listed in Table 25. The results indicate that the coefficient associated with pre-trip information differ significantly from the case without pre-trip information, implying that pre-trip information has a different impact on both departure time and route latent variables.

Model 4

In this paper by Fujiwara, Sugie and Zhang[24] the influence of pre-trip information on commuters, behavior is examined. The aim of this paper is to examine the effectiveness of new discrete choice model dealing with departure time choice and travel mode choice. Paired combinatorial model is developed to describe departure time choice behavior. Since PCL model can relax the restrictive independence of irrelevant alternatives property of the conventional multinomial logit model (MNL), the differential correlations between discrete times alternatives which are categorized by analysts can be implicitly be considered. Further, the PCL model has been expanded into nested PCL model, which has a hierarchical choice structure between travel mode and departure time choices. A SP survey was made on commuters between Higashi-Hiroshima and Hiroshima. The main modes for commuting were car and rail. Hypothetical travel situations were set up in a survey. Departure time was classified in four categories, based on the pilot survey of actual travel situations. Travel time and cost for the two modes, level of congestion, and crowdedness for rail were set up by departure time and shown in Table 26.

Table 9. An example of SP cards

Departure time	Travel mode & route	Travel time	Congestion	Travel cost	Option
- 6:30 am	Free road	70 mjn	0.5 km	free	1
	Toll road	45 min	0 km	800 yen	2
	Railway	40 min	have a seat	560 yen	3
6:30 am - 7:00 am	Free road	90 min	1.5 km	free	4
	Toll road	55 min	0.5 km	800 yen	5
	Railway	40 min	have no seat	560 yen	6
------	--				
7:20 am -	Free road	95 min	2.0 km	free	10
	Toll road	60 min	0.5 km	800 yen	11
	Railway	40 min	have a seat	560 yen	12

In the PCL model, the probability to choose option *i* is given by formula:

$$P_i = \sum_{j \neq i} P_{i/ij} P_{ij} \tag{31}$$

$$P_{i|ij} = \exp\left(\frac{V_i}{1-\sigma_{ij}}\right) \Bigg/ \left[\exp\left(\frac{V_i}{1-\sigma_{ij}}\right) + \exp\left(\frac{V_j}{1-\sigma_{ij}}\right)\right] \tag{32}$$

$$P_{ij} = \frac{(1-\sigma_{ij})\left\{\exp\left(\frac{V_i}{1-\sigma_{ij}}\right) + \exp\left(\frac{V_j}{1-\sigma_{ij}}\right)\right\}^{1-\sigma_{ij}}}{\sum_{q=1}^{n-1} \sum_{r=q+1}^{n} (1-\sigma_{qr})\left\{\exp\left(\frac{V_q}{1-\sigma_{qr}}\right) + \exp\left(\frac{V_r}{1-\sigma_{qr}}\right)\right\}^{1-\sigma_{qr}}} \tag{33}$$

Where:

- Pi/ij is the conditional probability of choosing option i given the chosen binary pair (i, j).
- Pij is the probability for the binary pair (i, j).
- σij is the index of similarity between alternatives i and j.

The PCL model is consistent with random utility maximization if the conditions 0≤ σij ≤1 are satisfied. If σij=0 for all pairs (i, j) then PCL model becomes MNL. Substituting lower two equations into first one, we have:

$$P_i = \frac{\sum (1-\sigma_{ij}) \left\{ \exp\left(\frac{V_i}{1-\sigma_{ij}}\right) + \exp\left(\frac{V_j}{1-\sigma_{ij}}\right) \right\}^{-\sigma_{ij}} \exp\left(\frac{V_i}{1-\sigma_{ij}}\right)}{\sum_{q=1}^{n-1} \sum_{r=q+1}^{n} (1-\sigma_{qr}) \left\{ \exp\left(\frac{V_q}{1-\sigma_{qr}}\right) + \exp\left(\frac{V_r}{1-\sigma_{qr}}\right) \right\}^{1-\sigma_{qr}}} \tag{34}$$

The estimation results for PCL are given in table for restricted and unrestricted cases. These models have four alternatives: before 6:30, between 6:30-7:00, between 7:00-7:20, and after 7:20. The unrestricted PCL case has the similarity parameters σij of all the pairs of alternatives, while the restricted PCL has three similarity parameters based on the “distance” between alternatives as follows:

σ1 = σ12= σ23= σ34   σ2= σ13= σ24   σ3= σ14

Where:

- σ1 is the similarity index between two subsequent alternative.
- σ2 is the similarity between every other alternative, and the
- σ3 is the similarity between the first and the last alternative.

It is known that departure time choice is influence by travel time and delay probability. Here is employed a simple variable “safety margin”, that is equal to the difference between work start time and the expected arrival time at the work place, in departure time choice models in addition to travel time attributes set up in SP experiment. The estimation results are listed in Table 27.

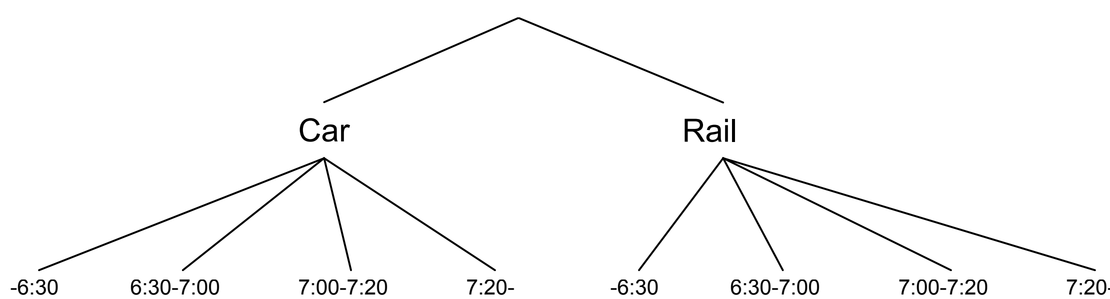

Figure 3. Hierarchical choice structure of nested PCL model

Table 10. Estimation results of departure time choice models

Variable			Unrestricted PCL model		Restricted PCL model		MNL model	
Travel time		[G]	-0.040	(2.16)	-0.037	(2.99)	-0.039	(1.81)
Safety margin		[G]	-0.046	(4.41)	-0.046	(3.93)	-0.050	(4.18)
Traffic congestion		[C]	-0.528	(0.99)	-0.575	(1.13)	-0.677	(1.11)
Crowdedness in vehicle[a)]		[R]	1.688	(4.90)	1.610	(4.27)	1.754	(4.91)
Constant		[1]	0.426	(1.23)	0.076	(0.24)	0.461	(1.59)
Constant		[2]	1.203	(4.01)	1.100	(2.89)	1.581	(4.89)
Constant		[3]	3.689	(6.68)	3.297	(5.47)	3.631	(7.22)
Similarity parameter	σ_{12}		0.000	(0.004)	-------		-------	
	σ_{13}		0.000	(0.01)	-------		-------	
	σ_{14}		0.647	(1.88)	-------		-------	
	σ_{23}		0.000	(0.11)	-------		-------	
	σ_{24}		0.587	(1.08)	-------		-------	
	σ_{34}		0.000	(0.002)	-------		-------	
	σ_1		-------		0.000	(0.00)	-------	
	σ_2		-------		0.250	(0.40)	-------	
	σ_3		-------		0.679	(1.66)	-------	
Initial likelihood[b)]			-231.5		-231.5		-231.5	
Maximum likelihood			-192.7		-197.1		-192.7	
Rho-squared			0.150		0.153		0.153	
% correct			55.1		55.1		55.1	
No of samples			167		167		167	

Parameter (t-value), [a)] =1, if possible to have a seat for rail; =0, otherwise, [b)] L(0), [G]:generic variable, [C]:car specific variable, [R]:rail specific variable, [1]:-6:30 specific variable, [2]:specific variable, [3]: -7:20 specific variable

A nested PCL model is developed, based by modifying PCL from the table in order to analyze travel time and mode choices. It includes hierarchical choice structure. Since PCL is in the logit family it is easy to expand to the nested model in the same way as the ordinary nested logit model. In the Figure 27, the hierarchical structure is assumed.The choice probability of alternative I in the nested model is:

$$P_i = P_{i|r} \cdot P_r$$

$$P_{i|r} = \frac{\sum_{j \neq i} (1-\sigma_{ij})(Q_{i.ij} + Q_{j.ij})^{-\sigma_{ij}} Q_{i.ij}}{\sum_{q=1}^{C_r - 1} \sum_{t=q+1}^{C_r} (1-\sigma_{qt})(Q_{q.qt} + Q_{t.qt})^{1-\sigma_{qt}}} \tag{37}$$

Where:

$$Q_{i.ij} = \exp\left\{\frac{aX_{ir}}{1-\sigma_{ij}}\right\} \tag{38}$$

$$P_r = \frac{\sum_{k \neq l}(1-\sigma_{kl})(D_{k.kl} + D_{l.kl})^{-\sigma_{kl}} R_{k.kl}}{\sum_{g=1}^{R-1}\sum_{h=g+1}^{R}(1-\sigma_{gh})(D_{g.gh} + D_{h.gh})^{1-\sigma_{gh}}} \tag{39}$$

Where:

$$D_{k.kl} = \exp\left\{\frac{(bY_k + \lambda_k L_k}{1-\sigma_{kl}}\right\} \tag{40}$$

$$L_k = \ln \sum_{i}^{c_k-1}\sum_{j=i+1}^{c_k}(1-\sigma_{ij})\left[\exp\left(\frac{aX_{ik}}{1-\sigma_{ij}}\right) + \exp\left(\frac{aX_{jk}}{1-\sigma_{ij}}\right)\right]^{1-\sigma_{ij}} \tag{41}$$

Where X and Y are vectors of explanatory variables, a and b are their parameter vectors, respectively. Lk is a log-sum variable and λ is its parameter. Table 28 shows the parameters in the nested PCL model.

The estimated parameters indicated that the informed level of travel service given by pre-trip information significantly affects the departure time choice. It was also shown that similarity parameters among alternatives are not statistically significantly in this SP study. The nested PCL is effective in describing the hierarchical choice structure between travel mode and departure time choice.

Model 5

In the paper of Guan and Nishii[25] is described a P&BR (Park and Bus Ride) system which should help to reduce congestion In Kofu area, Japan. A social experiment has been adopted for that purpose. A questionnaires were given to commuters participated in the experiment, and the data on the commuting behavior and Stated Preference data for the P&BR was obtained. Based on combined experiment data (ED) and SP data the model for estimating P&BR demand is proposed. During the experiment days, a questionnaire-based survey on P&BR system was conducted, to obtain data regarding their regular commuting behavior on the non-experiment days and SP data for the P&BR system. At the same time the commuting behavior of people who joined the list of test subjects but did not use system on experiment days and other commuters who did not join the list were surveyed to obtain ED data.

Table 11. Nested PCL models for usual departure time choice and travel mode choice

Variable		**Travel mode choice model**		**Departure time choice model**	
Travel cost (100yen)	[G]	0.476	(2.33)	-------	
Travel time	[G]	-------		-0.036	(1.90)
Safety margin	[G]	0.017	(1.41)	-------	
Traffic congestion	[C]	-------		-0.618	(1.23)
Crowdedness in vehicle [a)]	[R]	-------		1.332	(2.88)
Constant	[R]	2.087	(1.42)	-------	
Constant	[1]	-------		1.004	(0.90)
Constant	[2]	-------		1.910	(3.21)
Constant	[3]	-------		2.537	(4.98)
Similarity parameter	σ_{12}	-------		0.000	(0.0008)
	σ_{13}	-------		0.004	(0.032)
	σ_{14}	-------		0.000	(0.000)
	σ_{23}	-------		0.345	(0.279)
	σ_{24}	-------		0.545	(0.517)
	σ_{34}	-------		0.632	(1.268)
Log-sum parameter	λ	0.277	(3.80)	-------	
			[2.80]		
Initial likelihood [c)]		-115.8		-231.5	
Maximum likelihood		-53.3		-203.6	
Rho-squared		0.540		0.100	
% correct		91.0		50.3	
No of samples		167		167	

Parameter (t-value from 0) [t-value from 1], a), b), [G], [C], [R], [1], [2], [3]: See table 1

Based on the previous SP/RP combined models, the ED/SP model is proposed and where equation (41) defines each utility function of the ED model and equation (42) SP model:

$$u^{ED}_{in} = \beta' x^{ED}_{in} + \alpha' w^{ED}_{in} + \varepsilon^{ED}_{in} = \nu^{ED}_{in} + \varepsilon^{ED}_{in} \qquad (42)$$

$$u^{SP}_{in} = \beta' x^{SP}_{in} + \gamma' z^{SP}_{in} + \varepsilon^{SP}_{in} = \nu^{SP}_{in} + \varepsilon^{SP}_{in} \qquad (43)$$

u_{in}: utility for individual (n)'s alternative (i).

$\boldsymbol{v_{in}}$: deterministic term of utility for individual (n)'s alternative (i).

$\boldsymbol{\varepsilon_{in}}$: random term of utility for individual (n)'s alternative (i).

$\boldsymbol{x_{in}}$ *,* $\boldsymbol{w_{in}}$ *,* $\boldsymbol{z_{in}}$: explanatory variable vector for individual (n)'s alternative (i).

β', α', γ': unknown coefficient vector .

When log-likelihood functions of ED and SP models are expressed by equation (41), the jointly log-likelihood function of the ED and the SP model is expressed by the equation (42)

$$L^{ED}(\alpha', \beta') = \sum_{n=1}^{N^{ED}} \sum_{i=1}^{I_n^{ED}} \delta_{m}^{ED} \cdot \log(P_{ni}^{ED}),\ L^{SP}(\beta', \gamma', \mu) = \sum_{n=1}^{N^{SP}} \sum_{i=1}^{I_n^{SP}} \delta_{ni}^{SP} \cdot \log(P_{ni}^{SP}) \quad (44)$$

$\delta_{ni}^{ED,SP}$={1:choice (i) is selected; o: others}; N:sample size; i: number of choices.

$$L^{ED+SP}(\alpha', \beta', \gamma', \mu) = L^{ED}(\alpha', \beta') + L^{ED}(\beta', \gamma', \mu) \quad (45)$$

To estimate the jointly log-likelihood function, a step-by-step procedure estimation is proposed:

Step 1 By maximizing the log-likelihood function, obtain the estimates of **parameters of the SP model, μ^β' and μ^γ', before making the following calculation:**

$$\hat{t}^{ED}_{in} = \mu\hat{}\beta' \, x^{ED}_{in} \quad (46)$$

Step 2 The utility function of the ED model is as follows:

$$\nu^{ED}_{in} = \lambda t^{ED}_{in} + \alpha' w^{ED}_{in} \quad (47)$$

By maximizing the equation (46), obtain the estimates λˆ and α'ˆ before calculating the estimate of each parameter by using the following equation:

$$\mu\hat{} = 1/\lambda\hat{},\ \beta\hat{} = \mu\beta'\hat{}/\mu\hat{},\ \text{and}\ \gamma\hat{} = \mu\gamma'\hat{}/\mu\hat{} \quad (48)$$

The accuracy of estimates α', β' and γ' is improved by executing Step 3.

Step 3 To obtain scaled SP data, multiply x and z by μˆ. Pool SP and ED data to estimate SP and combined model simultaneously.

By applying the parameter estimation procedure in the above section, to the data regarding Table 29.

Table 12. Results of estimation procedure

		SP model		Combined model	
		β	t	β	t
		Kaikokubashi route			
Alternative peculiar dummy		0.4937	2.5825	0.3373	2.0706
Parking cost		0.4809	2.0466	0.6394	3.1764
Commuting time		-0.0406	-6.5249	-0.0205	-6.6728
Cost		-0.0003	-8.0745	-0.0002	-9.313
Scale parameter		-	-	1.88	4.986
		Shikishima route			
Alternative peculiar dummy		1.0339	3.9441	0.8701	4.0773
Parking cost		-	-	-	-
Commuting time		-0.0389	-5.4871	-0.0460	-6.2700
Cost		-2.87E-4	-7.2593	-3.00E-4	-8.7135
Scale parameter		-	-	0.92	5.6304
	Kaikokubashi route		Shikishima route		
	SP model	Combined model	SP model	Combined model	
Sample size	539	702	447	574	
L(□	-280.9	-335.67	-251.31	-292.27	
Hit ratio	0.6957	0.7393	0.689	0.7439	
ρ^2	0.2481	0.2691	0.1889	0.2654	

Further, sensitivity analysis was performed on Combined model and on SP model. Table 30 shows the four cases tested.

Table 13. Cases tasted on SP and Combined model

Case	Time slot	Parking cost
A	5-15 minutes	no charge
B	5-15 minutes	2000yen/month
C	10-20 minutes	no charge
D	10-20 minutes	2000yen/month

The change rate for P&BR demand in accordance with the change in the parking costs and the time gaps between buses arrivals are shown in Figure 28.

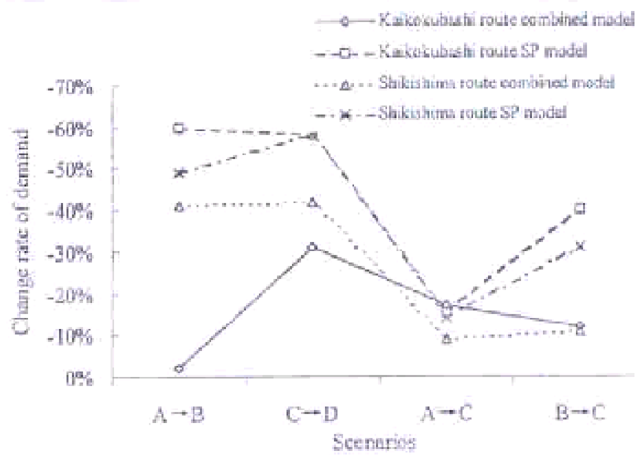

Figure 4. The results in two routes

These results indicate the SP model sensitively responds to changes and the combined model is stable against these changes.

<u>Modeling the impact of en-route information on drivers' behavior in Route-Choice.</u>

Model 6

Modelling the driver behaviour using a computing paradigm called *Intelligent Agent* is a new concept put forward by Dia, H. [(13),(26)]. This model was used in conjugation with traffic simulation component to evaluate the impact of providing drivers with real time information. This approach allows the modeling of interactions between drivers, coordinating their goals and updating of their decisions on real time and day-to-day basis.

In the *Intelligent Agent* paradigm each driver is modelled through and autonomous software component .An intelligent agent represents a person making a trip. Each intelligent agent is assigned a set of goals that must be achieved (for example, travel from point A to B at minimum cost) and takes input from a database of knowledge comprising of certain beliefs, intentions and preferences. The main advantage of using Intelligent Agents in travel behaviour modelling is that they are active entities that interact with their environment (for example, modify the action decisions based on the available real time traffic information) and in consort with other agents. The first requirement of this model is the identification of parameters that define each user. Suitable Parameters and their potential values would be obtained from the survey that was conducted on the peak-period automobile commuters travelling along a traffic commuter corridor in Brisbane, Australia.

Two types of questionnaires were selected to be distributed, out of which only the one that deals with en-route information is relevant to our study and will be discussed.

The survey will comprise of questions that will fall into the following categories:

1. Personal information: age, occupation, gender

2. Normal travel pattern: day-to-day behaviour such as work schedule, route choice and response to recurring congestion.

3. En route response to unexpected congestion information: do they change certain travel decisions.

4. Willingness to change driving patterns: What incentive is needed to do so?

The model consists of a commercially available microscopic traffic simulation model (PARAMICS) that will be used to simulate the commuter corridor. The traffic simulation will follow a deterministic fixed time step approach. The dynamic driver model would be used to direct individual vehicles on the corridor and will specify how a particular driver approaching a given node selects the next link to be taken. This output is provided to the traffic simulation model trough and Application programming Interface (API).

The model will be tested for various scenarios and compared to the base scenario which reflects the network condition without any ATIS strategy

Model 7

Another experiment using an interactive multi-user simulator that was developed at the University of Texas at Austin was conducted, to examine trip-making behavior in response to different information strategies of varying information quality and credibility [14].

First, in order to make the experiment realistic, some personal as well as travel related data were collected from the participants. The data collected shows that the average actual travel time to reach the workplace was 26 minutes. About 63.95 % of the participants reported tolerance to lateness in excess of 5 minutes. The average preferred arrival time was 19.6 minutes before work time began.

Using the above data, the experiment was set up to represent real life situation. Using the simulator, behavior data under various controlled situations of ATIS was collected form participants who were actual commuters.

Finally, the data was analyzed using regression model and the results were further verified and probed into by developing multivariate probit models.

Two principal objectives of the experiment were:

1. To model the compliancy behavior of ATIS users and ascertain the key factors that influence compliancy decisions. Specifically, the experiment investigates the association between switching decisions and compliancy decisions to determine the how the quality of supplied information affects the overall compliancy rate.

2. To investigate how different potential ATIS information strategies, characterized by a wide range of information quality and credibility, affect commuters' travel decision. The following three aspects were examined:

- Nature of information: Prescriptive vs. Descriptive
- Information quality: trip time information based on reliable prediction, prevailing conditions, perturbed prediction, differential predicted, differential prevailing and random.
- Feedback: own trip experience, recommended, actual best

Studies have been generally concerned with the users' immediate route choice decisions in response to supplied information. But such information however also influences the evolution of the traffic system through its effect on users' day-to-day decision process.

The set up of the study is similar to the set of many studies conducted in this area and can be read by referring to the paper

The objectives were achieved through the effect of the three experimental factors:

- The commuters who had access to ATIS system were given prescriptive or descriptive information and their reaction to this type of information was measured.
- In terms of information quality, 6 levels of information type from highly precise travel time to randomly generated travel time values are supplied.
- In terms of feedback, 3 levels of feedback are used: the first level displays users own experience such as the actual trip time, the second level displays the information on the recommended path along with the information in first level, the third level displays the information on actual best path in addition to information in the first level.

Two types of mathematical models were employed to analyze users compliance behavior and capture the effects of the characteristic strategies, the traffic system and the commuters on this behavior:

- Event-count models of the observed frequency of distribution.
- Discrete-choice models of individual decisions, to comply and follow traffic information received.

The first Poisson regression model was estimated to investigate the relative difference in behavior under the three experimental factors represented as binary indicators in the model. The results showed that the users tend to comply more with prescriptive information. Also a hierarchy of information quality tends to exist with the more reliable the information, the higher the rate of compliance. Third, the user complied more if he obtained a feedback of the actual best path followed by recommended path and least with just the information on his own experience.

A second Poisson regression model was estimated relating information quality, experience, information switching interaction, nature of information and post trip feedback to compliancy behavior. The estimators showed that overestimation and underestimation of estimated travel time significantly reduced the likelihood of compliance with underestimation having a greater negative effect. Next, the role of experience on compliance behavior was examined. First, the influence of recent experience and frequency of experience was predicted. The experiment showed a strong negative response to recent experience of traffic jam after the consumer changes routes. The experiment also showed that farther the distance, the system suggests that they divert, the less willing they are to comply. The proxy-switching cost is a highly influential variable.

In order to analyze the compliancy at a disaggregate levels, by modeling compliancy decision of individual user at each decision node, a multivariate probit model structure with embedded logit, model was developed. For further study on similar models the studies reference in Ben-Akiva and Bolduc(27) , Brownstone and Train(28) and Bhat(29). It was used to verify the above results and to provide a deeper insight into some of the underlying mechanisms of how users combine ATIS with past experience in the system. The estimates from this model had the same results as the regression models developed. In addition, the models showed that compliance not only depends on how accurate the information is but also on how frequently it is accurate. The model also showed that the greater number of switches to later departure times, higher the compliance.

Model 8

The paper by Polydoropoulou (30)**,** aims to understand how people deal with unexpected congestion during the *en-route* stage and how might they respond to ATIS. Travelers' route selection decisions were investigated through stated preference and revealed preference survey of Bay Area automobile commuters. Then binary logit models are developed to capture the variables and choices that affect the utility functions developed. We are interested in the model developed and the variables included and how this could be applied to our study.

On repetitive commute trips, individuals follow their pre-selected travel pattern. If the travel conditions differ from the expected and travel time exceeds certain thresholds, then they might decide to switch travel pattern. The choices open to travellers acquiring en-route information include route diversion and switching destination, mode and/or parking choice. This paper focuses only on the en-route decision to divert to an alternate route when travellers, through different types of information sources, become aware of unexpected traffic congestion.

Mail-back questionnaires were distributed to peak period automobile commuters crossing the Golden Gate Bridge in February of 1993.

It involved the collection of both Revealed Preference (RP) data on actual en-route travel response to unexpected congestion, and Stated Preference (SP) data in instances where the response to hypothetical ATIS scenarios was reported. The relationship between traveller response to qualitative, quantitative, predictive delay information, and prescriptive information given by hypothetical ATIS could then be modelled in combination with real-life (reported) behaviour.

The survey provided data on attributes of alternative choices (routes). These data are needed to develop a route choice model, which is sensitive to network performance and congestion delays, as well as ATIS characteristics. When faced with the hypothetical situation of having an in-vehicle ATIS device giving accurate delay information on the same trip, a majority of respondents were willing to use this information. Twenty seven percent of travellers would switch to the alternate route when qualitative information is provided to them. This increases to 52% under quantitative information for the usual route, 55% under predictive information for the usual route, 58% when delay information on usual route and travel time on best alternate route are available, and 61% under prescriptive information to take the alternate route.

A unique aspect of this research was the estimation of ATIS user response from a combination of two data types: 1) revealed preference (RP data), where the actual behavioural response to unexpected delay is reported and 2) stated preference data (SP data), where traveller behaviour in hypothetical ATIS scenarios is reported. RP and SP data were combined to address the validity issue inherent in using SP data The utility maximized by each traveller in the RP context is given by:

$$U_{RP} = V_{RP} + \varepsilon \tag{48}$$

Where V_{RP} is the systematic utility function influencing the RP decisions; and

ε represents the random utility components influencing the RP decisions.

The utility maximized by each traveller in the SP context is given by:

$$U_{SP} = V_{SP} + \gamma \tag{50}$$

where V_{SP} is the systematic utility function influencing the SP decisions, and

γ represents the random utility components influencing the SP decisions.

It is assumed that the non-measured components of the RP utility (ε) and the SP utilities (γ) are independently and identically Gumbell distributed, and the level of noise in the data sources is represented by the variance of ε and v. We define μ^2 to be the ratio of the variances:

$$\mu^2 = \text{var}(\varepsilon) / \text{var}(\gamma) \tag{51}$$

And therefore the SP utilities can be scaled by μ

$$\mu U_{SP} = \mu V_{SP} + \mu\nu \tag{52}$$

so that the random variable (μ γ) has a variance equal to that in the RP utility (ε). It is possible to use both RP and SP observations in a logit estimation procedure that requires equal variance across observations. However the SP utilities are scaled by an unknown constant μ, which needs to be estimated.

Thus, systematic utilities were defined as follows:

$$V_{RP} = \alpha' w + \beta' x + \delta' c \tag{53}$$

$$\mu_i V_{SPi} = (\alpha_i ' w + \beta' x + \gamma' z)\, \mu_i \tag{54}$$

where *i* denotes the specific ATIS scenario.

Vector w represents the dummy variables for the alternative specific constants of each model. All relative coefficients (α, α_i) are unconstrained. The SP constants capture the influence of each ATIS scenario on travellers' decisions. Therefore the comparison of the RP and the SP constants gives the en-route switching propensity due to information provided by ATIS.

Sharing β in both RP and SP models implies that trade-offs among attributes included in x are the same in both actual travel behaviour and the SP behaviour. In the model, the x vectors represent all travel related coefficients, such as travel time, expected delay, and congestion level on alternate route. These variables are not affected by the information provision, but are actual characteristics of the alternatives. Vectors c are specific to the RP model and include the cause of delay and information source variables used in the RP context.

Factors inherent in Stated Preferences are represented by z with the corresponding coefficients γ. In this study, a variable representing the actual choice, included in z, captures the effect of inertia or justification bias. The experience variables are related to the actual delay reported in the RP situation.

The RP portion of the model describes travellers' decisions when they become aware of unexpected congestion on their usual route. A binary logit model was estimated with the dependent variable being the choice among "switching to an alternate route" and "do not change travel pattern."

The following section describes the specification of the variables. The variables included in the model are: 1) Travel time, 2) Expected delay, 3) Congestion on alternate route, 4) Knowledge of travel times, 5) Trip direction, 6) Cause of delay, and 7) Existing information sources.

The SP portion of the model examines commuter response to ATIS. The utility function of each SP model is given in equation (53). The stated preference is a categorical dependent variable, denoted by y, and represented by:

y = 1 if the response is “definitely take usual route”;

y = 2 if the response is “might take usual route”;

v = 3 if the response is “can’t say”;

y = 4 if the response is “might take best alternate route”; and

y = 5 if the response is “definitely take alternate route”.

The dependent variables have five categories, therefore four threshold values, $\theta_{1,}$ $\theta_{2,}$ θ_3 and θ_4 can be identified in the utility scale. The probabilities are given by:

$P(y= 1) = P\ (\mu\ U_{SP} <= \theta_1)$,

$P(y=3) = P(\theta_1 < \mu\ U_{SP} <= \theta_2)$,

$P(y=3) = P(\theta_2 < \mu\ U_{SP} <= \theta_3)$,

$P(y=4) = P(\theta_3 < \mu\ U_{SP} <= \theta_4)$,

$P(y=5) = P(\mu\ U_{SP} >= \theta_4)$

Since the SP utility functions have an intercept, one of the four threshold parameters is not identifiable, so the first one is arbitrarily set equal to zero.

The SP model specification is similar to the RP model specification. Travel time, expected delay, congestion on alternate route, and knowledge of travel time variables are shared between RPs and SPs. The SP model differs from the RP model in terms of the absence of the actual cause of delay (which was tested and found statistically insignificant in the SP scenarios) and the actual information sources (fixed as ATIS in the SP scenarios). The SP models include three new variables. A dummy variable that captures inertia/justification bias is included in the SP experiment; The variable takes a value of 1 if the alternative route was chosen under the RP situation and 0 otherwise. It is expected that travelers who switched routes in the RP situation, are likely to report taking an alternate route in the SP scenarios to justify their prior actual choice. To capture the effect of knowledge regarding traffic conditions, given travelers actual choice. two variables are created: 1) A variable equal to the actual delay experienced if the respondent switched routes in the RP situation. It is expected that the more delay the traveler experienced on the alternate route, the less likely he or she is to switch to the alternate route in the SP scenarios. 2) A dummy variable equal to 1, if the actual delay experienced was higher than the initially expected delay on the usual route, and 0 otherwise. It is expected that travelers who used their usual route and experienced more delay than expected will be more prone to switch in the SP scenarios. The bounds of the SP scenarios are unrestricted among the SP models.

Results of this study are as follows:

1. The more elaborate information on delay on the usual route (from qualitative, to quantitative, to predictive), the more likely travelers are to take the alternate route.

2. ATIS' suggestion to take the best alternate route in an unexpected delay situation results in increased probability of route change. This means that a priori people have a propensity to comply with ATIS suggestions.

3. Quantitative information for both usual and alternate route has the maximum effect on travelers' decisions to switch to an alternate route. This reflects the travelers' preference to make an informed decision rather than comply with ATIS instructions.

4. Travel time is negative and statistically significant, meaning that travelers will choose the alternative with the lowest expected travel time.

5. The longer the expected delay on the usual route, the more likely travelers are to change route.

6. Perceived congestion on the alternate route slightly reduces the possibility of taking an alternate route,

7. The source of information has a significant effect. Travelers are more likely to switch to an alternate route when they became aware of the delay by radio only, or when they become aware of the delay first by radio and then by their own observation, compared with observation and then radio, or observation only.

8. Drivers are less likely to switch to an alternate route on their home-to-work trip.

9. Weather as a cause of delay reduces route diversion probability. This might be explained by the fact that adverse weather affects the whole transportation network; travelers tend to stay on their usual route, with the expectation that route diversion may not save travel time

10. People who switched to an alternate route in the RP situation are more likely than others to switch in the SP scenarios.

The results show that with accurate delay information, commuters can overcome their behavioral inertia when faced with unexpected congestion.

If the response to various types of ATIS messages is not well understood then it can cause either a spatial transfer of congestion, or worse, lead to increased congestion. Traffic operations managers and ATIS designers must account for the different responses that specific ATIS messages might cause in incident

The basic theory states that behavioral response is predicated by stages of conflict arousal and motivation. Arousal is the stimulation that evokes reaction; motivation is the behavior that effects reaction. Arousal and motivation stem from an internal need to fulfill goals and the resultant activities are a function of all variables that arouse and direct behavior. The response will be influenced by (1) the amount of arousal, (2) the motivation of decision maker during choice, (3) factors of the problem domain, and (4) associations among cognitive elements. A primary factor in predicting an individual's response to conflict arousal is a function of behavioral situations.

Model 9

The conflict assessment and resolution theories popularized in psychology applied by Adler (5) in understanding of en-route driver behavior. Central to the formulation are two basic suppositions: (1) a driver's actions are directed toward meeting a set of travel goals, and (2) changes in behavior occur only as a direct result of the driver's perception that these travel goals will not be achieved. Decisions to divert or otherwise change from original travel plans occur when a threshold of tolerable conflict is exceeded, and the driver perceives an alternate course of action that would reduce the perceived level of conflict below that threshold. Assessment and response to conflict arousal directly relate to the driver's abilities to perceive and predict network conditions in conjunction with familiarity of network configurations and accessible alternate routes.

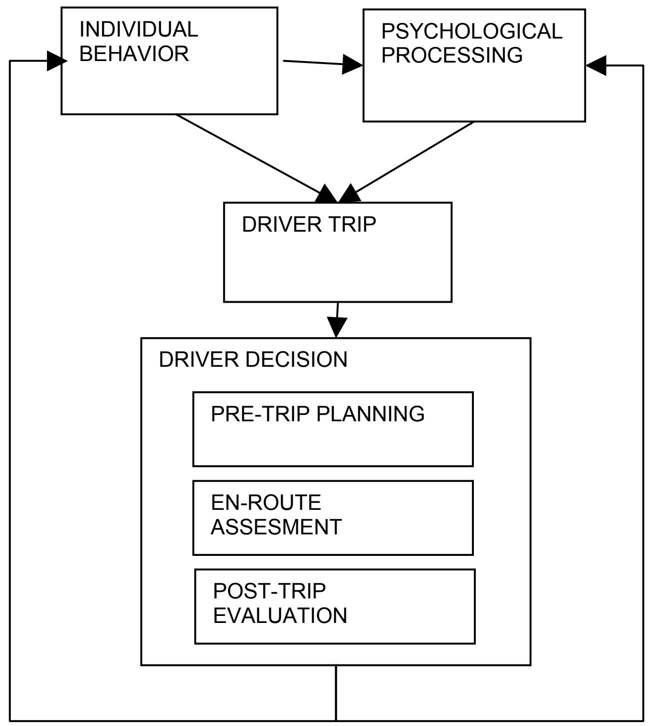

Figure 5. General Schemas for Driver Behavior

To test the approach, an interactive computer based driving simulation, FASTCARS (Freeway and Arterial Street Traffic Conflict Arousal and Response Simulator), was developed. FASTCARS integrates a driver simulation program with the conflict model approach to create a data collection tool for analyzing en-route driver behavior personal thresholds to tolerable conflict, the degree of conflict severity above which people attempt to respond to the situation.

Individual behavioral differences and experiences lead to the specification of different threshold levels between decision makers. Literature suggests that through increased experience, individuals learn to endure larger degrees of conflict. Over time, threshold to conflict severity also increases as individuals are more certain and comfortable with their experiences.

The proposed framework for modeling en-route driver behavioral choice is based on conflict theory and is constructed through the relationships between driver behavior, cognitive processing abilities, and components of the decision making process shown as in Figure29. The general approach suggests that travel is defined by three stages: pre-trip planning, en-route assessment and adjustment, and post-trip evaluation. The first two stages involve direct decision making in real-time. The third stage is a longer-term evaluation of past trip-making success creating the link between past performance and future impression that shapes driver behavior over time.

Although the focus of this research was en-route behavior, to enable a complete modeling approach it is important to consider pre-trip and post-trip decision process as these affect the en-route choices of the trip maker.

The author proposes that en-route travel is characterized by 4 main components: (1) initial travel strategies (defined in pre-trip planning), (2) conflict arousal and motivation, (3) information acquisition and processing, and (4) travel adjustment. The en-route decision process is depicted in Figure 30.

Modeling effort

During pre-trip planning, a driver establishes a set of goals to be achieved. The relative importance of goal attainment is defined by a set of preference weights attributed to each goal. Depending on the units that measure each goal, the decision-making process may be specified as either singly objective (e.g., minimize cost) or multi-objective (e.g., balance a set of conflicting goals measured in varied units such as cost and time).

For a given trip i at time t, the set of travel goals, $G^{it}{}_{d}(X)$, for driver d can be given as:

$$G_d^{it}(X) = [G_{1d}^{it}(x1), G_{2d}^{it}(x2), \ldots\ldots\ldots, G_{gd}^{it}(xg)] \qquad (55)$$

Where:

G_{gd}^{it} (x_g) = Travel goal g for driver d at time t for trip I

x_g = Set of performance indicators for goal g

Although drivers approach route choice differently, the decision process may be modeled by standard modeling methods. For this analysis, a *Weighted Objective Decision Method* was assumed. In this model, the objectives are ranked according to preference and relative weights are assigned in proportion to the strength of preference. Utility for a specific route or link is measured by the additive sum of the expected value of the goal attainment level multiplied by the relative weight. The selected alternative is the one that maximizes the expected utility,

$$\hat{U}^r = \sum_{g=1}^{G} W_g \hat{V}_g^r \qquad (56)$$

Where:

Error! Objects cannot be created from editing field codes. = Total predicated utility for route r

W_g = Relative weight for goal g

$\hat{V}_g^r$ = Perceived expected value for goal g on route r

In the formulation above, the value of goal attainment for a specific route is based on a driver's perception and prediction of travel conditions and associated utility levels. For any trip at a given time there is an actual value of utility V for a route, however, this value of utility is unknown to the driver. Instead, each driver bases his decisions on some perceived level of utility. This perceived utility may be stated as the actual utility biased by personal behavior (e.g., risk) and an uncertainty factor ρ such that:

$$\hat{V}_g^r = \rho_g^r V_g^r \tag{57}$$

The parameter ρ is a function of the driver's behavior, experience, and knowledge of the route and the system. At each time t + At, driver's cognitive processing is updated which in turn changes the factor ρ = ρ + Δρ·

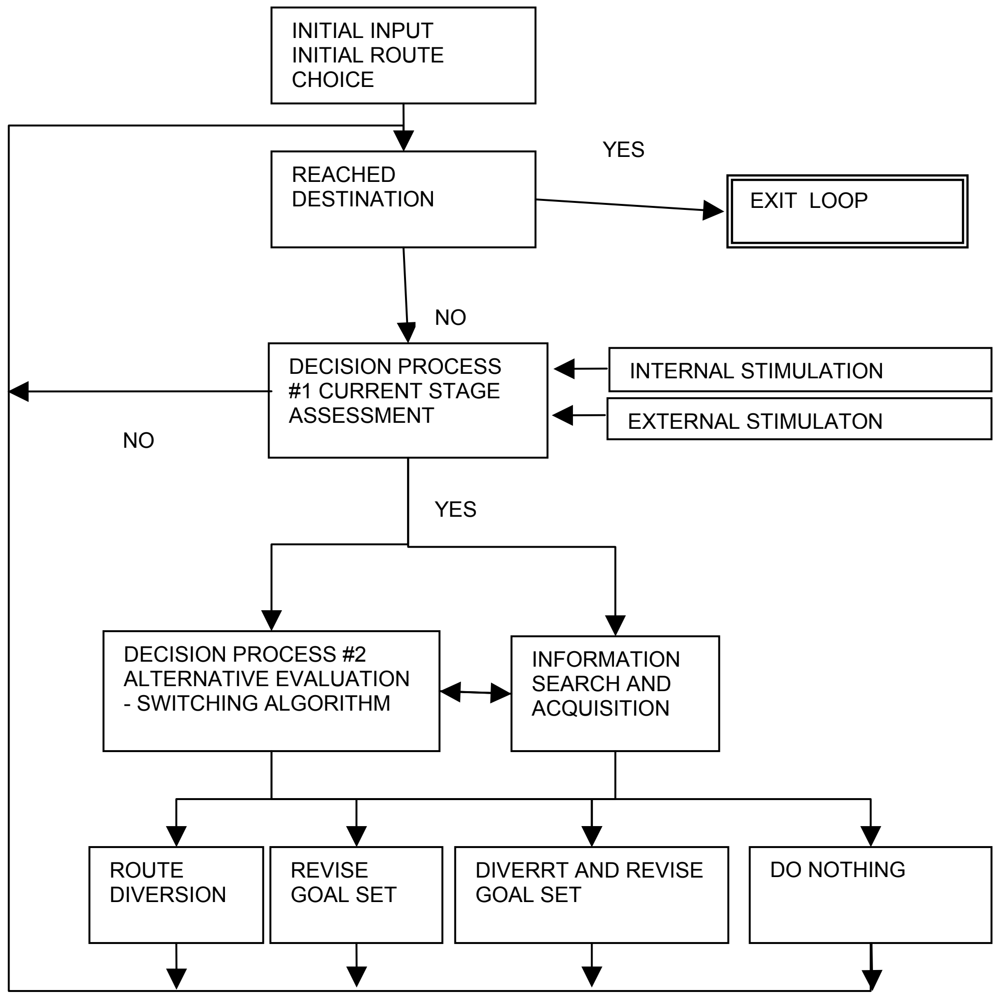

Figure 6. General schema for driver behavior model

As the trip maker is traveling trough the chosen route, he periodically evaluates his progress towards attaining his goals. The assessment phase is initiated when drivers become more uncertain that their goals may not be met if they were to continue on the current path under the current travel conditions. As travel conditions change, and the conflict levels increase, the desire to alter travel behavior becomes more apparent. The threshold to conflict tolerance may be defined as the level of overall utility for a given route, below which the route becomes undesirable, or:

$$\hat{U}^r < U^r \tag{58}$$

Where:

$\hat{U}^r$ = Threshold utility level for route r

U^r = Perceived utility on route r

One significant conflict arousal has been inflicted, the trip maker responds by either diversion of route or goal revision. Response is triggered by high arousal and motivation. Diversion occurs under high motivation; goal revision under low motivation. Both responses are based on the ability to reduce conflict and improve the utility of travel.

High motivation occurs when drivers project that diverting to an alternate path i will result in a significant gain in marginal utility. Diversion will occur if the perceived utility on the alternate path \`i' is greater than the utility projected for the current path \`c' by some improvement threshold η:

$$\hat{U}^c + \eta < \hat{U}^j \tag{59}$$

Several factors impact both the prediction of utility and switching propensity Mahmassani and Jayakrishnan[31]. First, there is some inherent uncertainty associated with estimating utilities. With imperfect information of travel conditions, the prediction is based on limited perception and memory. The inertia resulting from uncertainty that refrains many drivers from switching paths is based on the risk-taking behavior of drivers defined earlier by the parameter ρ.

Often motivation to switch depends on the set of alternatives. Under high conflict but low motivation it is possible that drivers will remain on course but revise the weights of the goal set. Adjusting the level of expectation through a reordering of the weights may reduce the levels of anxiety and frustration that was increasing as a result of the inability to meet previously defined objectives (i.e., reduce cognitive dissonance). If W represents the new ordering of weights on the objective space, the revised utility of the current course of action is:

$$Max(U'^c + \eta, U'^j) \tag{60}$$

These weights may change in response to conflict several times during the course of a trip. It is likely that the experience will lead drivers to rethink the initial ordering of the weight set and to consider which orderings were more effective in reducing conflict during the trip.

FASTCARS, in conjunction with the modeling framework proposed, is an interactive computer-based simulator that has been developed for in laboratory experimentation to gather data for estimating and calibrating predictive models of driver behavior under conditions of real-time information. The simulation integrates a model of multi-objective goal specification and evaluation, a hypothetical traffic network, simulated real-time information technologies, and interactive driver travel choices. FASTCARS is designed to model en-route travel decision-making. FASTCARS provides an artificial environment that replicates spatial and temporal situations that arouse conflict and motivation during travel. The combination effects of perception, conveyed through visual representation of traffic conditions, and prediction, through real-time information availability, form the background choice domain. A scoring and evaluation format, based on weighted additive utility models, provides a basis for analyzing behavior and preference. The experimental set up in FASTCARS can be reviewed in detail by referring to this paper.

FASTCARS has provisions for VMS within its simulation environment, and hence can be effectively and easily adopted to study the effect of Parking and Transit Information on drivers.

Model 10

In this experiment [15] data was collected using a simulation-assignment model based on the corridor network version of DYNASMART model that includes en-route path switching. All user responses are directly input into this model, thus the traffic conditions are presented in real-time. The simulator comprises of three main components: the traffic performance simulator, the network path processing component and the user decision-making component. The traffic performance component is a fixed time step mesoscopic simulator. This component process the link trip time and delays and provides this as input to the network path processing component which in turn calculates the path time. This information is given to the user and data on path switching decisions is recorded. The setup of this experiment can be reviewed from the paper.

45 participants were randomly recruited and their behavior studied. From post-experiment questionnaire it was seen that 95.6% of the participants perceived the information as accurate and about 76% tended to adopt the information for future use.

Next, a model of the decision process that determines en-route path switching as a function of users cumulative and recent experience with the system was developed and calibrated using multinomial probit framework. This took into account the traveler’s learning from the past experience with the system and captured the serial correlation arising from repeated decisions made by the same traveler.

The model is based on the theory that commuter ‘i’ does not switch routes or path as long as the corresponding trip time saving TTS_{ijt} (at decision node j on day t), which is the trip difference between the current path TTC_{ijt} and the best path TTB_{ijt} remains within the commuters route indifference band IBR_{ijt} as follows:

$$TTS_{ijt} = TTC_{ijt} - TTB_{ijt} >= 0, \; j = 1,2,3,4,5,\ldots.N \quad t = 1,2,\ldots\ldots.T \tag{61}$$

$$\phi_{ijt} = \begin{cases} -1 & if \quad 0 \le TTS_{ijt} \le IBR_{ijt}, \\ 1 & otherwise. \end{cases} \tag{62}$$

Φ_{ijt} (j=2,3,4,5…N) equals 1 when user switches his or her path at decision node j, with Φ_{ijt} equals –1 otherwise.

From the model proposed in (Mahmassani and Jayakrishnan[(31)])

The above model can be adopted and the new equation is:

$$\phi_{ijt} = \begin{cases} -1 & if \quad TTS_{ijt} - TTB_{ijt} \le \max[\eta_{ijt} TTC_{ijt}, \pi_{ijt}], \\ 1 & otherwise. \end{cases} \tag{63}$$

Where

$$\eta_{ijt} = g_r(X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,r} \qquad \xi_{ijt,r} \approx MVN\;(0, \Sigma\xi_r), \tag{64}$$

$$\pi_{ijt} = g_r(X_i, Z_{ijt}, \theta_{ijt}) + \xi_{ijt,r} \qquad \xi_{ijt,m} \approx MVN\;(0, \Sigma\xi_m), \tag{65}$$

η_{ijt} represents the relative indifference band, as a fraction of the TTC_{ijt}. π_{ijt} denotes the corresponding minimum path time savings, from decision node j to the destination, necessary for the user I to switch from the current path on date. Both quantities are random variables, with the mean values anticipated to vary symmetrically with the users' characteristics and experience to date. As such, both quantities consist of systematic and random variables.

The systematic component of relative indifference band and the minimum time savings are $g_r()$ and $g_m()$ respectively. They depend on user's inherent attributes X_i and vector of performance characteristics Z_{ijt} experienced by user 'i' upto decision point j on day t, θ_{ijt} is a vector of parameters to be estimated. The random terms $\xi_{ijt,x}$ and $\xi_{ijt,m}$ are assumed to be normally distributed, with zero means and general covariance structure.

Comparing Eqns. (61) and (62), the expression for indifference band for en-route switching is obtained as follows:

$IBR_{ijt} = \max [\eta_{ijt} TTC_{ijt}, \pi_{ijt}]$

Based on research the specifications of the route switching band consist of the following components:

1. initial band
2. user characteristic component
3. information reliability component
4. myopic component
5. scheduled delay component
6. unobserved component.

For the purpose of analysis, the variables included in the en-route behavior model are as shown in Table 31.

Table 14. Variable definitions for the indifference band in joint departure time and route switching model

Element	Definition
AGE_i	Age of commuter i, 1 if age<20: 2 if 20<=age<=39; 3 if age 40<=age<=59; 4 if age >60
$GENDER_i$	Gender of commuter i, =1 if male; =0, if otherwise
$ERRO_{ijt}$	Over-estimation error provided by real-time information; the relative error between actual travel time and travel time reported from the system when actual travel time is shorter then reported travel time
	$ERRO_{ijt}=\max\{(RTT_{ijt}-ATT_{ijt})/ATT_{ijt},0\}$
	ATT_{ijt}:actual trip time from node (j-1) to node j
	RTT_{ijt}:reported trip time provided by real-time information for commuter i from node (j-1) to node j
	For pre-trip decision (j=1)
	$ERRO_{i1t}$: average error from origin to destination on day (t-1)
	$ERRO_{i1t}=(ERRO_{i2t-1}+...+ERRO_{i5t-1}+ERRO_{i6t-1})/5$
	$ERRO_{i6t-1}$:relative over-estimation error from node 5 to the destination in day (t-1)
$ERRU_{ijt}$	Under-estimation error provided by real-time information; the relative error between actual travel time and travel time reported from the system when actual travel time is longer then reported travel time
	For en-route decision (j=2,3,4,5)
	$ERRO_{ijt}=\max\{(ATT_{ijt}-RTT_{ijt})/ATT_{ijt},0\}$
	For pre-trip decision (j=1)
	$ERRO_{i1t}=(ERRO_{i2t-1}+...+ERRO_{i5t-1}+ERRO_{i6t-1})/5$
$SERRO_{it}$	Sum of the values of over-estimation error provided by real-time information including pre-trip and en-route on day t-1
	SERROit=($ERRO_{i2t-1}+ERRO_{i3t-1}+...ERRO_{i6t-1}$)

Element	Definition
	$ERRO_{i6t-1}$: relative over-estimation error from node 5 to the destination in day (t-1)
$SERRU_{it}$	Sum of the values of under-estimation error provided by real-time information including pre-trip and en-route on day t-1
	$SERRU_{it}$=($ERRU_{i2t-1}$+$ERRU_{i3t-1}$+...$ERRU_{i6t-1}$)
	$ERRO_{i6t-1}$: relative under-estimation error from node 5 to the destination in day (t-1)
λit	A binary indicator variable, equal to 0 if D_{it}=D_{it-1}
ΔTRit	The difference between travel times of commuter i has adjusted between day t and t-1(min)
ΔDTit	The amount of departure time that commuter i has adjusted between day t and t-1 (min)
$SDPE_{ijt}$	Early-side schedule delay relative to commuter's preffered arrival time for commuter i at decision node j on day t (min)
	$SDPE_{ijt}$=max{PAT_i-RAT_{ijt},0}
	PAT_i: preferred arrival time for commuter i
	RAT_{ijt}: predicted arrival time for commuter i from node j to destination according to the travel time provided by the real-time information system (RAT_{ijt}=$CLOCK_{ijt}$+TTC_{ijt})
	$CLOCK_{ijt}$:current clock time for commuter I at node j on day t
$SDPL_{ijt}$	Late-side schedule delay relative to commuter's preferred arrival time for commuter i at decision node j on day t (min)
	$SDPE_{ijt}$=max{RAT_{ijt}-PAT_i,0}
ω_{it}	A binary indicator variable, equal to 1 if SD>=0 (early-side), or equal to 0 if SD<0 (late-side)
κ_1	A binary indicator variable, equal to if j=1 (pre-trip route decision), or equal to 0 if j=2,3,4,5 (en-route decision)
a's,b's,c's,d's	parameters to be estimated
τ_{it}	error term of departure time switching indifference band for commuter i on day t
$\xi_{ijt,r}$, $\xi_{ijt,m}$	error term of route switching indifference band for commuteri at node j on day t(η_{ijt}, π_{ijt})

$IBR_{ijt} = \max[\eta_{ijt} TTC_{ijt}, \pi_{ijt}]$, *j=1,2,3,4,5* (66)

$\eta_{ijt} = \kappa_1 a_1 + (1-\kappa_1) a_2$ *Initial band* (67)

$+ a_3 GENDER_i +$ *User characteristic component*

$a_4 ERRO_{ijt} + a_5 ERRU_{ijt}$ *Information reliability component*

$+ a_6 SDPE_{ijt} + a_7 SDPL_{ijt}$ *Schedule delay component*

$+ \xi_{ijt,r}$, *Unobserved component*

$$\begin{aligned}
\pi_{ijt} &= \kappa_1 b_1 + (1-\kappa_1) b_2 && \textit{Initial band} \\
&+ b_3 GENDER_i + && \textit{User characteristic component} \\
&b_4 ERRO_{ijt} + b_5 ERRU_{ijt} && \textit{Information reliability component} \\
&+ b_6 SDPE_{ijt} + b_7 SDPL_{ijt} && \textit{Schedule delay component} \\
&+ \xi_{ijt,m}, && \textit{Unobserved component}
\end{aligned} \tag{68}$$

The model parameters were estimated using a special purpose maximum likelihood estimation procedure that relies on Monte-Carlo simulation to evaluate the MNP choice probability.

The results of this experiment are:

- females exhibit a wider mean indifference band than male commuters for en-route path switching.
- trip makers become more prone to switch routes when the system provides under-estimated trip time information than when the system provides over-estimated trip time.
- commuters tend to switch routes in response to higher difference between the predicted arrival time at the destination node and their own preferred arrival time

<u>Modeling the impact of transit information on travelers' behavior.</u>

Model 11

Very few studies have studied the effect of transit information system on traveler behavior. This study [32] attempted to do so. It deals with commuter perception of transit services available to them, their level of familiarity with it and the potential impact of transit information system on the propensity of commuters to use transit who currently do not use transit. For this study a stated preference survey of the users of Santa Carla and Sacramento counties were conducted through computer aided interviews. Different questionnaires were prepared for transit and non-transit users. A methodical definition of transit and non-transit users was prepared for this study as shown in Figure 31. For further information on the methodology used to conduct the survey, the paper should be read in detail.

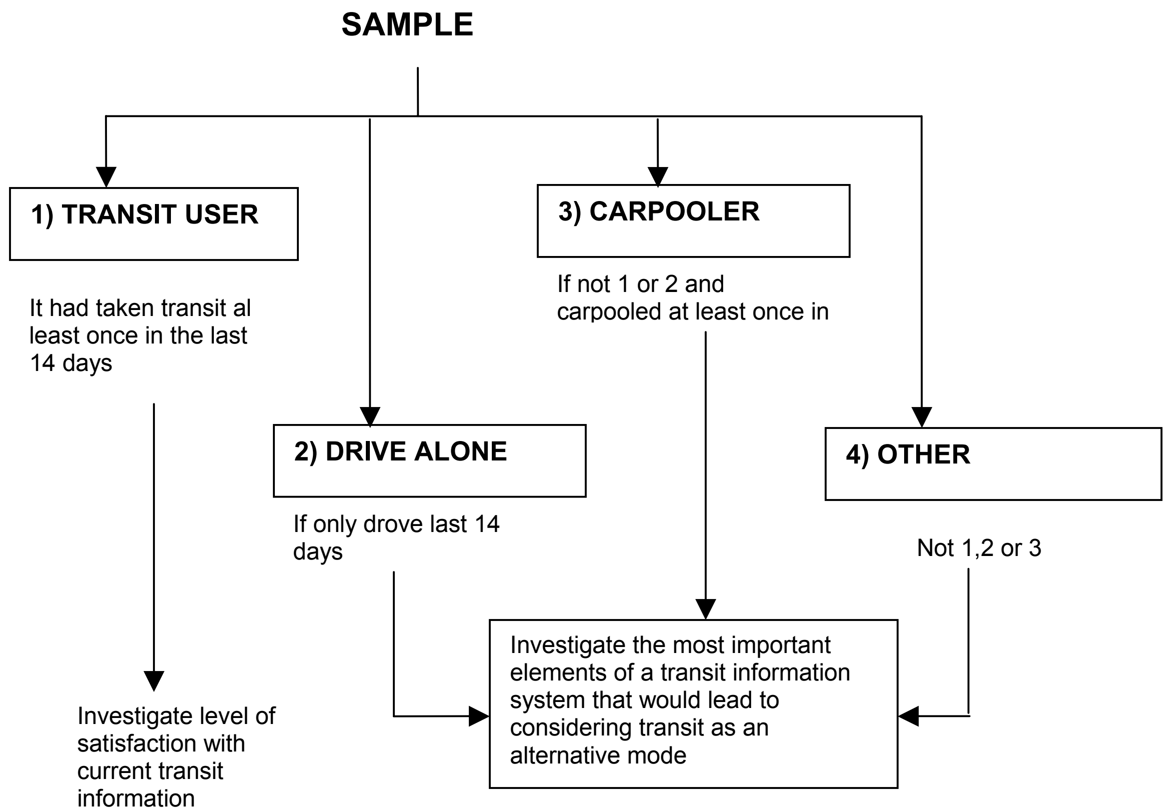

Figure 7. Basic branching in survey design

The following information was obtained from each correspondent:

- General commuter characteristics, including travel time, flexibility of work starting time etc.
- Traffic information that the respondents receive
- Commuters' perception of transit service in their area.
- The most important types of transit information that commuters desire and its potential impact on propensity to use transit.
- Stated-preference choice set that investigates the likelihood that non-transit users will use transit if the desired information is available.
- Detailed information about transit use for transit users.

- Level of satisfaction the transit users regarding the availability of different type of transit information, identifying the most important information desired by each respondent.

- Demographic and socio economic data.

- Familiarity with transit service.

The results of the survey showed that 80.5% drove alone, 10.5% carpooled, 4.4% took transit and about 4.6% either road a bicycle or walked. The average travel time was 24.75 minutes. Statistical test showed that richer people used transit lesser.

The reasons for taking transit were as stated in this order from maximum preference to minimum are:

- car unavailable every day

- saves money

- dislike driving

- don’t own a car

- don’t have to pay for parking

- keeps air clean

- difficulty finding a parking space at work

Table 15. Main reasons for taking transit to work

Car unavailable every day	10 (24.39%)
Saves money	6 (14.63%)
Dislike driving	4 (9.76%)
Saves time	3 (7.32%)
Don't own a car	2 (4.88%)
Don't have to pay for parking	1 (2.44%)
Keeps air clean/people have to do their part	1 (2.44%)
Difficulty finding a parking space	1 (2.44%)
Undecided/Don't know	2 (4.88%)
Other	11 (26.83%)
Total	41 (100%)

In this study a majority used bus service (68%) while train and light rail accounted for 12.5%.

Also the study indicates that commuters who live relatively closer to transit stops use transit and about 26% drove to it. Also a majority (83%) indicated that they wait less than 10 minutes or less on an average for transit service. About 48% had monthly pass and 36% paid for each ride.

It is also noted that 38% of non-transit users indicated that they might consider transit of more information was available

Transit users were also asked to name the tree most important items of transit information that needed to be improved and Park and Ride information was ranked as the first most important by 4.5%, 2nd most important by 2.6% and third most important by 6.2% of transit users.

To investigate the potential impact of transit information on commuters' willingness to use transit, a stated-preference survey of non-transit users was conducted. The travel time by transit was customized for each respondent based on actual travel time previously given in an interview. The travel time by transit was the respondents travel time multiplied by a factor (0.75,1.00, 1.25, 1.50). This factor was generated randomly. The response was scaled from 1 to 10: 1 denoting extremely unlikely to use transit and 10 denoting extremely likely to use transit.

In order to model the choice of non-transit users towards transit use, if certain information about transit use was available to them, an ordered probit model was used. This model was chosen from among various alternative models because it can model a dependent variable that takes more than two values when these values have a natural ordering.

The dependent variable is unobserved and is expressed as

$$Y^*_I = \beta' x_i + \varepsilon \tag{69}$$

Where Y* = dependent variable coded as 0,1,2,3,……

β = vector of coefficients

xi = vector of independent variables

ε = error term, normally distributed N[0,1]

The dependent variable is observed as the likelihood to use transit, therefore let

$$\begin{aligned}
&Y = 0 \text{ if } Y^* <= 0\\
&Y = 1 \text{ if } 0 <= Y^* <= u_1\\
&.\\
&.\\
&.\\
&.\\
&Y = j \text{ if } u_{j-1} <= Y^*
\end{aligned} \tag{70}$$

The threshold values μ_j and the coefficient vector β are unknown and need to be estimated.

For a normal distribution the probability that Yi falls into the jth category is given by

$$P(Yi = j) = \Phi(\mu_j \quad \beta' x_i) \quad \Phi(\mu_j \quad \beta' x_i), j = 0,1,\ldots\ldots J \qquad (71)$$

This model was run and the results were as follows:

- As the travel time by transit increased, commuters were less likely to use transit
- Commuters who already used carpool had a higher likelihood of using transit
- Respondents over 70 years of age had a higher likelihood of using transit.
- Respondents who had a lot of control over their work starting time were less likely to use transit.
- Women are less likely to use transit
- Owning no car increases the probability of using transit.

<u>Modeling the impact of parking information on drivers' choice of parking</u>

Model 12

In the paper by Amy E Hester[(33)], Advanced Parking Management Systems using variable message signs to provide drivers with up-to-date information on the number of open spaces at selected parking lots throughout a city has been analysed.

The aim of the paper was to focus on the behaviour rules that govern drivers' performance when choosing among parking lots. But what is relevant to our study is the mathematical model developed to capture the drives decision process towards parking after reading the VMS and the variables involved in the model.

Studies have suggested that parking choices would be a function of factors that reflect the environment and the decision maker Thompson and Richardson[(34)]. Factors that reflect the environment include the in-vehicle travel time, time to drive to the parking lot plus find a space within the lot, egress time i.e. time to walk from the parking lot to some final destination, parking fee at a lot, expected fine when parking illegally outside a lot, and expected time spent queuing at the parking lot entrance.

The study believes that the drivers' decisions are risky ones in this case, because the outcomes of a given choice are not always known with certainty. For example, based on the parking availability information on a VMS, a driver located at some distance upstream of several different possible lots will choose to park in one particular lot and then head toward that lot. However, when the driver arrives at the chosen lot, the lot might have become filled. Thus, at the time the driver makes a decision to park in a particular lot, it is not known which of the two outcomes will occur—the lot is full or the lot is not full. In this context, the driver might decide to combine the utilities of the outcomes of a particular choice in order to have some standard for comparing one risky decision to another.

A mathematical model based on utility was developed and tested. The decision to park in a particular lot was made more or less risky by varying the number k of open parking spaces at the lot and, therefore the probability $p(k)$ that the lot would be available when the driver arrived was assumed. Additionally, in order to approximate the load actually placed on the driver, participants had to navigate a virtual roadway while making their parking lot decisions, using an advanced driving simulator to present the actual stimuli. The set up of this experiment can be referred to by reading the paper. Two sets of experiments were conducted. Experiment 1 tested several plausible alternative versions of the expected utility EU theory. The results from this first experiment were consistent with the assumption that drivers minimized their expected travel time.

Experiment 2 dealt with the theory that describes the choice between several parking lots and is not relevant to our study. Hence only Experiment 1 will be discussed here.

In Experiment 1, three different versions of the EU theory were tested. First, one assumed that some or all drivers attempt to minimize the expected travel time to a given lot (METT decision rule). Second, one might assume that some drivers attempt to minimize the walking distance from the lot to the final destination (MWD decision rule) Finally, one might assume that some drivers attempt to minimize the time spent waiting at a lot for a parking space or, equivalently, they attempt to maximize the parking availability (MPA decision rule). In each parking scenario with several alternative lots, drivers were told as to how far it is to each lot, how long they will have to wait if the lot is full, long a walk it is from each lot to the destination, and how many spaces are available in each lot.

Thus, it is simple then to determine for each scenario which lots would be chosen by drivers trying to MWD or MPA. However, it cannot so quickly decide which lot in a scenario drivers trying METT would choose. Here we need to define several additional terms. Let Tij(k) represent the travel time to lot i with k open spaces when the destination is building j. Let $t_{d(i)}$ equal the driving time to a lot i, let $t_{w(ij)}$ equal the walking time from a lot i to a destination j, and let t_q equal the waiting time in a queue at a lot if that lot were full when the driver arrived. Finally, let *p*(*k*) equal the probability that a lot with *k* available spaces displayed on a

VMS will be open when the driver actually arrives at the lot. It is assumed for the study, that the number of total spaces in each lot is identical across lots as is the waiting time, t_q, at a lot and the probability, *p*(*k*), that a lot with *k* available spaces will be open. The expected total travel time is a weighted average of the travel time when the lot is not full and the travel time when the lot is full

$$E[Ti\ j(k)] = p(k)[\,t_{d(i)} + t_{w(ij)}] + [1 - p(k)][\,t_{d(i)} + t_{w(ij)} + t_q] \tag{72}$$

In order actually to predict the expected travel time in Eq.(71) for each lot in a given parking scenario, the walking, driving, and waiting times as well as the probability *p*(*k*) that lot *i* is open when *k* spaces need to be known or estimated. The times that we give to the participants in the study was used directly but p(k) needed to estimated. A realistic probability function is the one in which participants perceive nearly a 0% likelihood of arriving at a lot and finding it open, if there is less than some criterion number of open spaces in the parking lot. Above this criterion number, the perceived likelihood may rapidly increase as the number of open spaces increases until it reaches another, larger criterion number of spaces at or above which participants may perceive a nearly 100% likelihood of finding a lot full upon arrival. This relationship between the likelihood that a lot is open and the number of available spaces can be traced out by a power function with two parameters α and β.

$$p(k) = \frac{1}{2} + \frac{1}{2}\left[\frac{\beta^{(k-\alpha)} - \beta^{-(k-\alpha)}}{\beta^{(k-\alpha)} + \beta^{-(k-\alpha)}}\right] \tag{73}$$

The shape of the function is much like the shape of the cumulative distribution of the normal. Manipulation of the parameter a in the above function adjusts the inflexion point in the curve. Manipulation of the parameter b adjusts the steepness of the ascent of the function from the *x*-axis. The parking scenarios in Experiment 1 were designed so that the three potential decision rules could be clearly differentiated. This was accomplished by creating a subset of scenarios where each strategy predicted the choice of a different lot. A computer algorithm was developed to identify the values of α and β that maximized the agreement between participants' responses and the decisions consistent with the METT choice rule The maximum agreement was found with α equal to 8 and β equal to 1.6. The participants' responses overall were more often consistent with the decision to minimize the expected travel time (93.5%) than they were either with the decision to minimize the walking distance (78.3%) or the decision to maximize the parking availability (24.3%). The percentages do not add to 100, because in many of the scenarios two or more of the decision rules lead to the same lot choice.

Network Development

The network used for the implementation of the intermodal traffic assignment model that was part of this project was an extraction of the I-80 corridor in North New Jersey. The development of the transportation network data model took required a substantial effort, because of its size and because of the incompleteness of the data that were available. The data model development consisted of:

- Road network development;
- Bus Routes;
- Park and Ride facilities;
- Rail Network;
- Demand nodes;
- Intermodal capabilities.

Road Network development

Sources

We have received road network data from three sources: 1) Transportation planning data from the North Jersey Transportation Planning Authority (NJTPA) (green in Figure 32) and from the corresponding software that was developed for the North Jersey transportation planning model; 2) GIS data that was already integrated within the TransCAD software (black in Figure 1); 3) NJDOT GIS data; 4) NJDOT Straight-line diagram data.

Data Model Issues

There are two main issues regarding the road network data:

1. *The level of detail of the topology/geography.* Bus routes cover not only major highways but also local roads. In order to represent the bus service realistically, the bus routes, bus stops and the associated bus schedule had to be included in the network. The geography of the NJTPA data was not detailed enough, so the bus routes had to be inserted into the network that was built in the TransCAD software. From Figure 1, it can be easily seen that the TransCAD data provide much more detail than the corresponding NJTPA data, which is a highly aggregated network.

2. *The availability of the data for the attributes of the links that is necessary for the analysis.* The main link attributes that are necessary for the static traffic assignment and mode choice are the speed limits and the capacities of the links. The data built in TransCAD did not have any of these link attributes where the

NJTPA data as well as the NJDOT straight-line diagrams had those attributes. Since the NJTPA network was too aggregated for this implementation and in some cases containing errors, for new links that had to be added into the network or modified, the corresponding link attributes had to be found and embedded into the new network database.

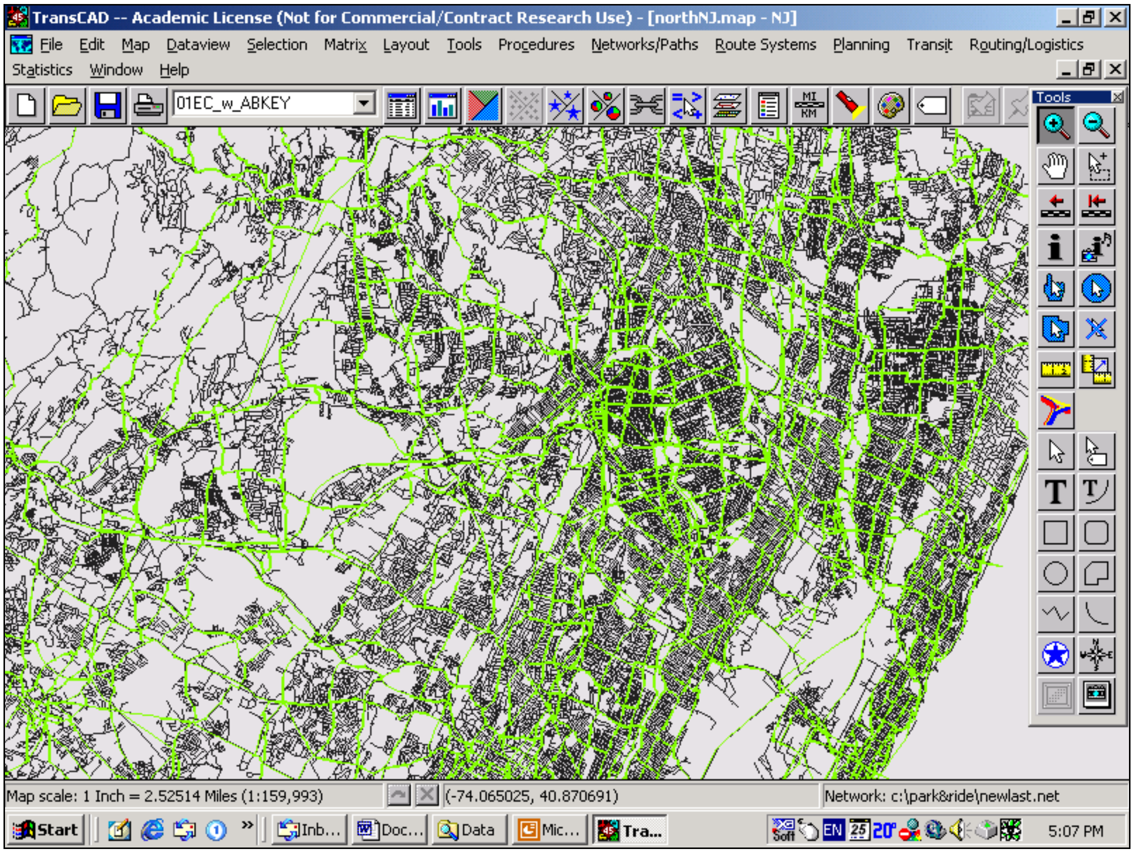

Figure 8. GIS of the Test Network

Data Model Development

Network Connectivity

The level of detail possessed by the TransCAD built-in data was determined to be too detailed for the implementation of a prototype traffic assignment model. The computational requirements for such a detailed network would have been tremendous. Furthermore, the inclusion of these local streets into the model would have needed the corresponding link and node attributes that were not readily available and would have required substantial data retrieval and integration effort.

Instead an aggregated TransCAD network data model was developed by creating buffers around major highways and around bus routes (pink color, Figure 33). This approach resulted in an aggregated network (Figure 34 – green lines show the buffers created) that incorporated the bus routes and major highways.

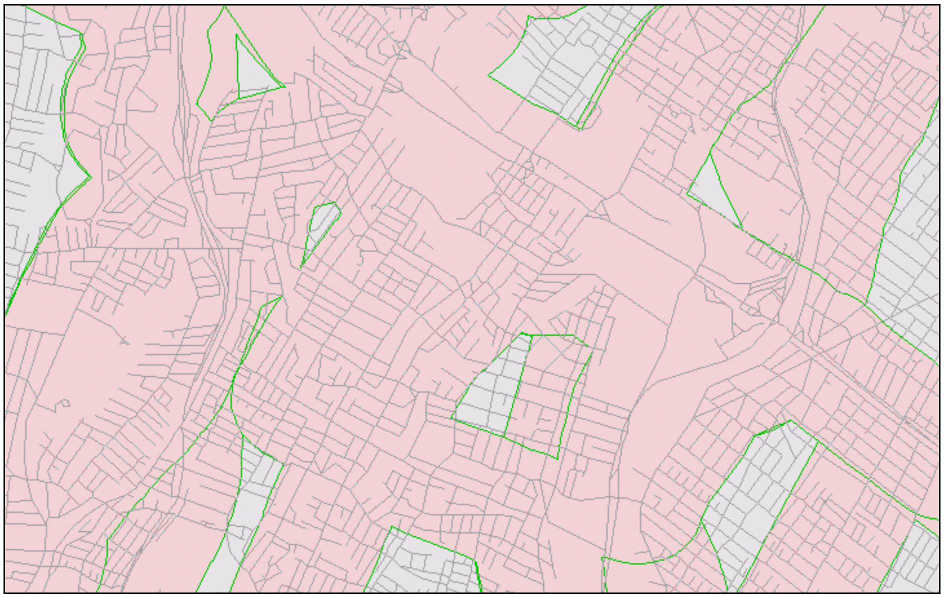

Figure 9. Aggregated TRANSCAD network

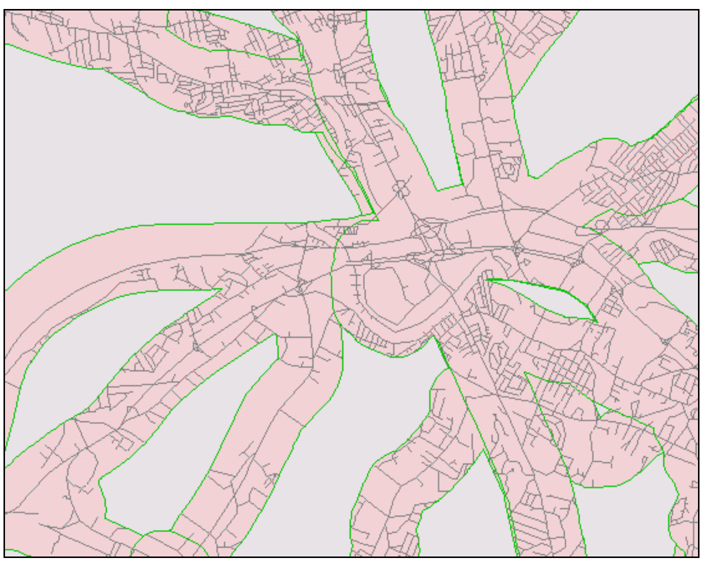

Figure 10. Further-Aggregated TRANSCAD network

This network had to go under some further “cleaning” since it contained parts of local streets. Also it was important (for operational model) that all exiting ramps are kept in order to allow traffic to go out. The final editing resulted in the network depicted in Figure 35.

Figure 11. Finalized Aggregated Network

Another challenge in building the network data model was network connectivity. The geography of the NJTPA network had many missing links that were affecting the connectivity of the model network – Necessary for routing applications that are embedded into the traffic assignment model. For example, a big segment of the I80 was missing. This segment was incorporated by using the TransCAD network. Also some geography was not correct and those links had to be corrected. For example, the ends of two neighboring links were not connected and they had to be joined. As part of this effort, approximately 1200 link segments and their associated attributes were incorporated manually into the original NJTPA network. The link attributes (speed limit and capacity) themselves were retrieved from the NJDOT straight-line diagrams data. Figure 36 depicts the links (red color) that were either added or modified in the link database.

Figure 12. Link segments that were added to achieve network connectivity

Bus Routes

The criteria followed for inclusion of the bus routes into the network were:

1. Bus route service's the I80 corridor,

2. Interconnects with Morristown and/or Boonton Rail line,

3. Has at least one Park and Ride facility along its route.

The bus routes were retrieved from the NJ Transit's website (Figure 37). We emphasize here that NJ Transit has bought the GIS database for New Jersey from Navigational Technologies Inc. that is more up to date for navigational applications. In addition, they incorporated their bus and train routes and associated schedules into their GIS database. The drawing was not to scale that made our task more difficult; therefore, the street names were used to provide the main orientation. Also, the way the TransCAD network database is constructed is not suitable for entering long bus routes precisely. This was due primarily to the fact that the roadway between adjacent intersections is comprised of many segments where each one of them had to be selected and integrated into the new database manually. All together 32 bus routes were entered into the aggregated GIS database for this project (Figure 38).

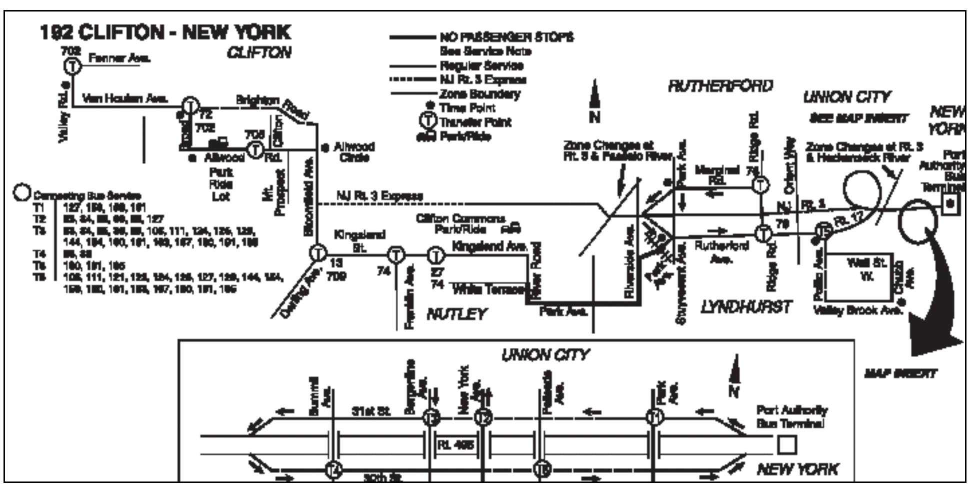

Figure 13. Sample bus route 192 Clifton-New York

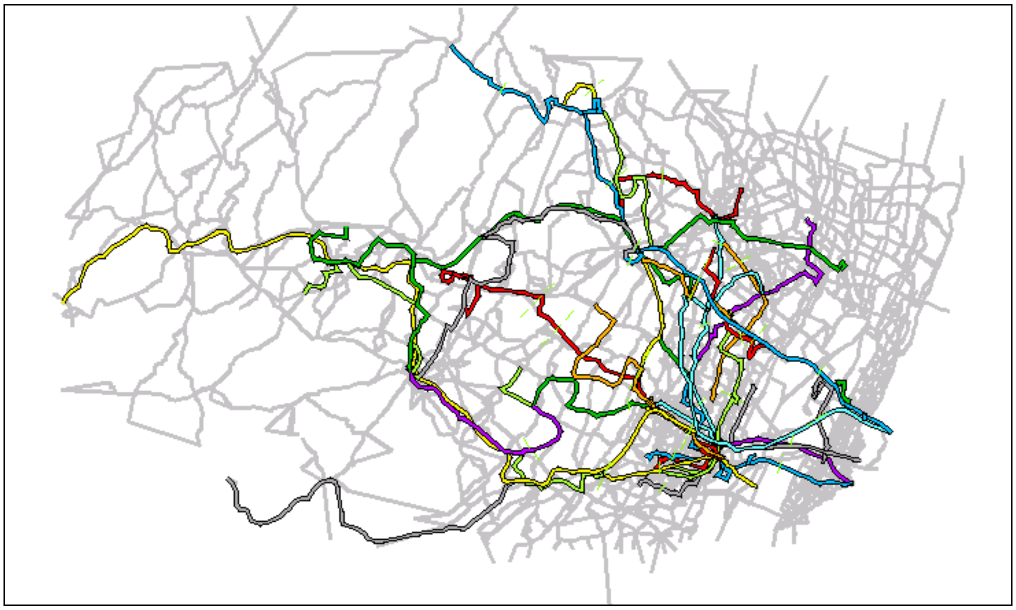

Figure 14. Bus routes included in the network model

The bus stop stations were also retrieved from the NJ Transit's website. We note here that this database is incomplete because the posted bus stations on the bus schedules as well as the web site contain only a partial list of the actual bus stops. The locations of the bus stops along a bus route was determined by the corresponding street names listed in the web site and the bus schedules. The ones whose location was described by landmarks, were much harder to locate. The resulting GIS bus stop location is shown in Figure 39.

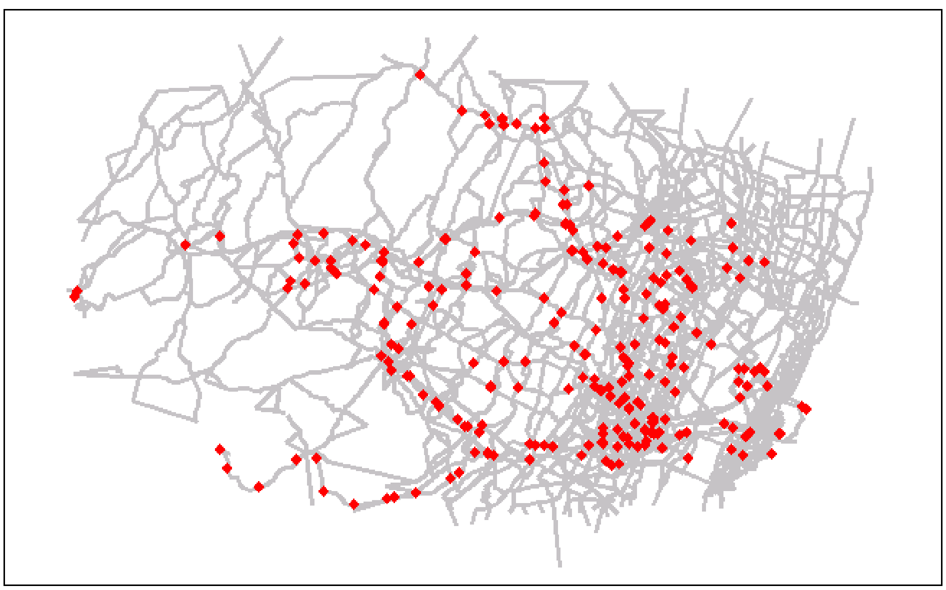

Figure 15. Bus Stops included into the network model

Park and Ride facilities

The data for Park and Ride locations was received from NJDOT database. The locations were described by addresses. Some of the addresses were precise enough so they were geocoded (located by GIS) immediately. However, more than 60% of the P&R facilities could not be located easily requiring substantial manual work.

Atlantic City Service Area	7/25/2000	Garden State Pa	41.4	4 miles north of Atlantic City Expressway. Can also ac
Atlantic City Expressway Intercept	8/1/2000	Atlantic city expr	4	Adjoining Atlantic City Expressway information center
Atlantic City Bus Terminal	8/1/2000	Atlantic City Exp		Ohio and Artic Avenue (station at michigan and atlantic)
Montvale Railroad Station	7/24/2000	N/A		Railroad Ave/Grand Ave
Route 17 Park & Ride	8/16/2000		17.6	Route 17 South
Walnut Place	8/16/2000			Walnut Street & Franklin Ave
Franklin Lakes VFW 5702 Park & I	8/7/2000			Pulis Ave & Franklin Ave
Hillsdale Railroad Station	8/2/2000			Washington Ave
Park Ridge Park & Ride	8/2/2000			Hawthorne & Park Ave
Park Avenue Park & Ride	8/2/2000			Broadway & Park Ave
Harrington Park Park & Ride	8/14/2000			La Roche Ave & Elm St.
Ramsey Railroad Station	7/31/2000			Main Street & Maple Street
Montvale Park & Ride	7/24/2000	Garden State Pa		Located on center median, between GSP North and adj
Cottage Place	8/16/2000			Cottage Street & Franklin Avenue
River Edge Rail Road Station	8/21/2000			River Edge at Rail Road Station
Oradell Town Green	8/16/2000			Oradell Ave & Maple St.
Emerson Park & Ride Lot	8/14/2000			East Emerson Ave
Oradell Park & Ride	8/16/2000			Oradell Ave & Church St.
Woodcliff Lake Railroad Station	8/2/2000			Broadway Ave
Veldran Avenue Commuter Parking	4/10/2002		0	Municipal Building on Oradell Avenue
Rutherford Railroad Station Park &	8/29/2000			Erie Avenue & Park Ave
Wyckoff Baptist Church Park & Ric	8/7/2000			Russell Ave & Wyckoff Ave

Figure 16. Sample P&R Database

That was the case for example for the P&R facility marked in Figure 40. It gives us the landmark, but not the exact location. In order to find the exact address, we first search the web, found the exact address and then embedded it manually into the GIS database. Also there were problems regarding different road street (road) names in the software database and the data that provided by the NJDOT. Overall, we had problem with the locations of more than 50 P&R locations that needed extra effort for integrating them into the data model.

A total of 81 P&R facilities were located in the study area in North Jersey, which are depicted in Figure 41. We note though, that this is not a complete set of all the P&R facilities in the area.

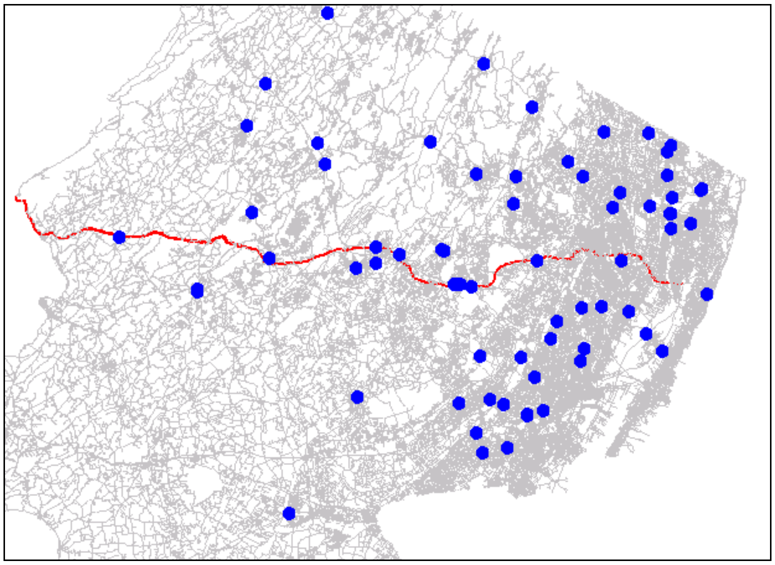

Figure 17. P&R Facilities in North Jersey

Rail Network

The main NJ Transit rail lines operating in North Jersey are presented in Figure 42. They included stations that are on the Boonton and Morristown Rail lines (see Figure 42). The NJ Transit rail lines that were built in the TransCAD GIS database were selected and imported into the new data model. The exact locations of the rail stations were retrieved from the NJ Transit's web site and integrated into the data model utilizing the geocoding capabilities of TransCAD (Figure 43).

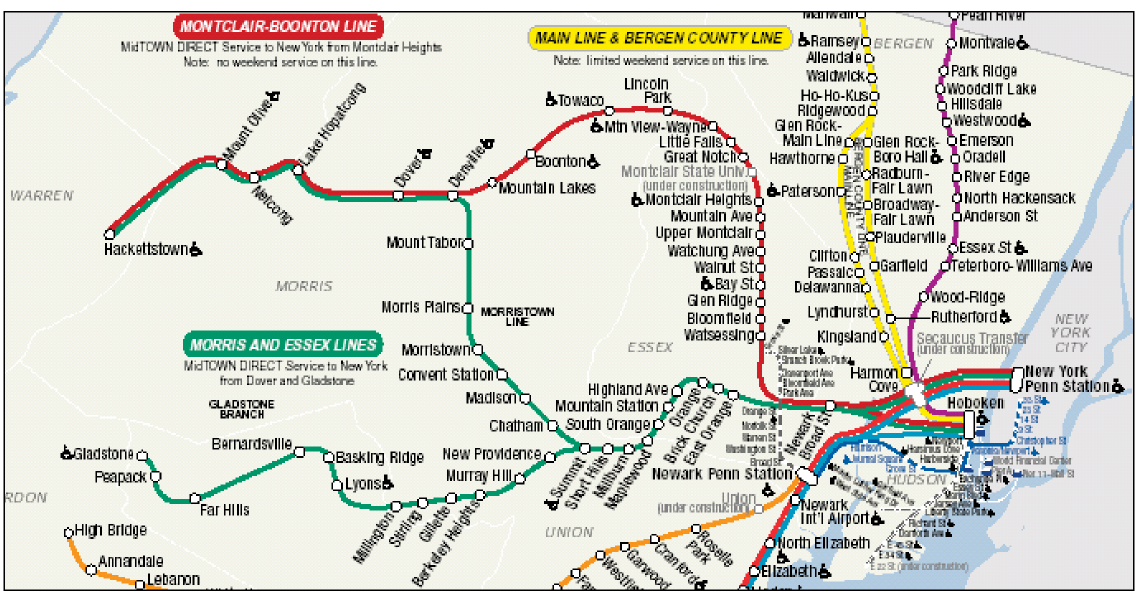

Figure 18. NJ Transit rail lines in North Jersey

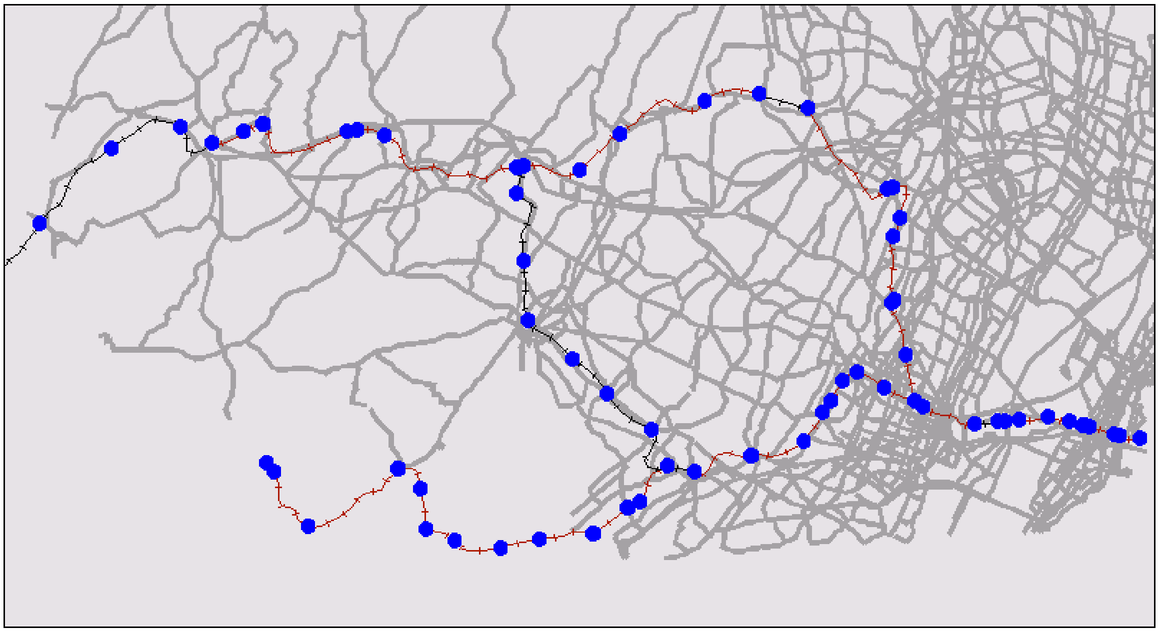

Figure 19. Rail line Stations integrated into the network model

Demand Data

The original NJTPA transportation planning model was enhanced to include additional demand nodes. These new demand nodes have been created as centroids of census tracts that cover the wider area of the network. Those nodes were then connected to road layer so the demand could be assigned to paths (Figure 44) as needed by the traffic assignment model.

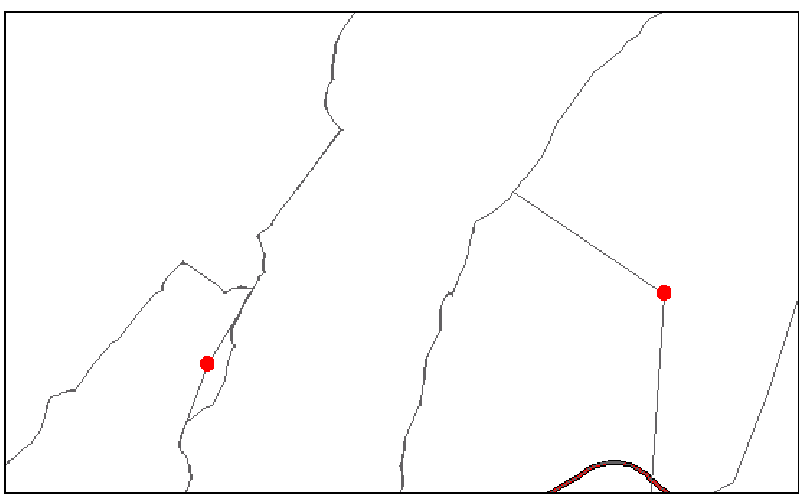

Figure 20. Sample new demand nodes embedded into the network model

The traffic demand that was built in the NJTPA transportation planning model for North Jersey was used to estimate an OD Matrix utilizing TransCAD's *OD Estimation feature.* The method used was User Equilibrium. Through that procedure, traffic flows that are in the network were used to project OD Matrix.

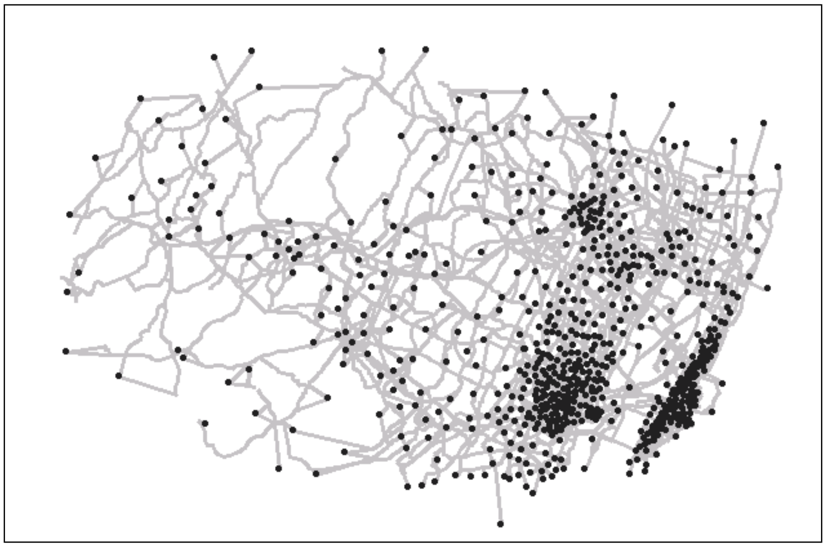

Figure 21. OD nodes in the network model

Intermodal Capabilities

One of the major contributions of this research was the incorporation of the intermodal P&R users (auto plus bus or auto plus train). In order to be able to model these intermodal paths, the park-and-ride feature had to be incorporated into the model. This P&R nodes were connected to the road line layer using the TransCAD option *Connect* and they became a part of the underlying node layer of the road line layer. In order to activate the P&R feature of TransCAD, the P&R facilities were first selected, second the transit network was created, and third the *Park-and-Ride* option was selected that set them as P&R transit stations.

When the TransCAD *Multiple shortest paths* feature is used, the software produces the shortest path (including the path travel time) from each user's origin to the P&R facility of interest.

The *Mode Split* module of TransCAD was executed and applied to the OD matrix to estimate the demand for each mode and OD pair. From this output, the corresponding demand for each P&R facility was estimated.

The *Traffic Assignment* module is based on the User Equilibrium principle and produces the OD path for each type of user such as auto only, bus only, walk plus bus/train, auto plus bus/train and walk plus bus plus train.

Mathematical Model

This model deals with intermodal network and by that with intermodal paths. In order to be able to predict demand for those paths and park-an-ride facilities, which is purpose of this project, the model had to include drive access to public transit. Since, this is not the only way to access public transit and there are similarities among the alternatives (walk and drive access to the public transit) and because the assumption of independence is violated, the multinomial logit model cannot be applied. In the chart are shown alternatives available in our network.

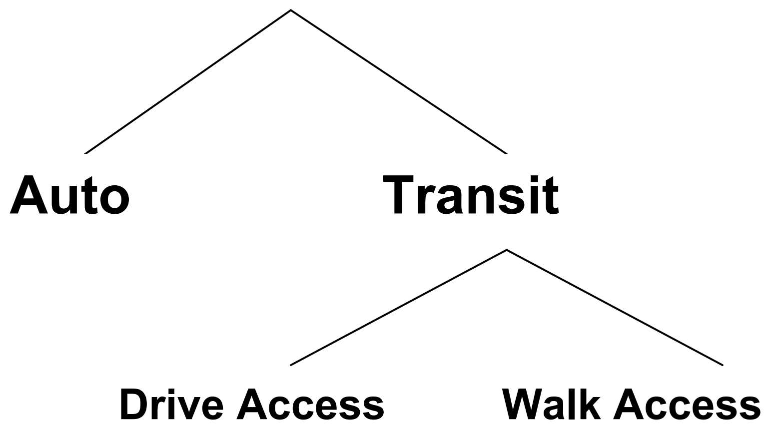

Figure 22. Nested Choice Model (NLM)

The Nested Logit model (NLM) relaxes that assumption of independence and because of that is applied here. The utilities for different modes in NLM are shown in the following equations.

$$Utility\_of\_Auto = \beta_{\log sum} * \ln(e^{Utility\_of\_Auto}) \tag{1}$$

$$Utility\_of\_Transit = \beta_{\log sum} * \ln(e^{Utility\_of\_Walk\_Access} + e^{Utility\_of\_Drive\_Acces}) \tag{2}$$

$$\beta_{\log sum} = 1 \tag{3}$$

Since in Auto option, there is just one option, the function **ln** does not have any impact, while it has in the Transit case. There was no data for β_{logsum}, so for simplicity, it is assumed to be 1.

The relevant parameters and the coefficients are taken from the Model 5 in the literature search, proposed by the Guan and Nishii. The variables and coefficients are shown in Table 33.

Table 16. NLM Parameters – Model 5

Explanatory Variable	Value
Alternative peculiar dummy	0.4937
Parking cost subsidies	0.4809
Commuting Time	-0.0406
Cost	-0.0003

Further, those explanatory variables and coefficients for different alternatives were applied to our network. Alternative peculiar dummy can be treated as a constant in a utility functions, once the alternative is chosen. Parking cost subsidies are calculated as a waived parking cost in that area. For example, if the parking cost for a whole day parking is $5, then the user of a park-and-ride facility has free parking and the charge is waived. This is reasonable, because in the most park-and-ride facilities in NJ parking is free or it is waived if the ticket for public transit is bought. Commuting time for transit option was calculated as a sum of Access_Time (Walk or Drive Access) and Travel_time. Travel_time is consisted of Transfer_times, Wait_time, In_Vehicle_Time and Egress_time. Transfer Time was not included since realistic data could not be obtained. Commuting Time in Auto option was calculated as a free flow time from origin to destination. Cost for the Transit option was calculated as a fare price for the shortest transit path. Cost in the Auto option was calculated as a parking price at the destination. The following equations represent our model. In the next chapters these values of the coefficients represent the base case of utility functions:

$$\text{Utility\_of\_Transit\_Walk\_Access} = 0.4937 - 0.0406 * \text{Travel\_Time} - 0.0003 * \text{Cost(Fare)} - 0.0406 * \text{Walk\_Time} \tag{3}$$

$$\text{Utility\_of\_Transit\_Drive\_Access} = 0.4937 - 0.0406 * \text{Travel\_Time} - 0.0003 * \text{Cost(Fare)} - 0.0406 * \text{Drive\_Time} + 0.4809 * \text{Parking\_Cost\_Sub} \tag{4}$$

$$\text{Utility\_of\_Auto} = 0.4937 - 0.0406 * \text{Drive\_Time} - 0.0003 * \text{Cost(Parking)}$$

The marginal probabilities of Auto and Transit are calculated using the logit probability equation using Nested Logit Model option, with the utilities specified on the top of the page. When these probabilities were applied to the OD matrix, the total demand between each OD for each of the three modes (auto, transit with walk access and transit with drive access) is calculated.

Sensitivity Analysis

There are several types of pre-trip information that has to be examined. Sensitivity analysis was used and several scenarios developed in order to determine the impact of various pre-trip information. The results of all scenarios are then compared to the results of base scenario and from there can be found which type of information had the biggest impact.

Scenarios 1&2-Testing the impact of pre-trip information on parking availability

Impact of Information on parking availability on commuters is represented by increasing parking subsidies coefficient in the model. This is done since it would have similar effect as giving parking availability information to the commuters and that is increased propensity to use park-and-ride facilities because of eliminated uncertainty about parking.

In the Scenario 1 coefficient was increased by 25% and in the Scenario 2 coefficient was increased by 50%. The exact values of coefficients are shown in Table 34.

Table 17. Parking Subsidies Coefficients

	Parking subsidies coefficient		
Scenario 1	0.4809	--->	0.601125
Scenario 2	0.4809	--->	0.721350

Scenarios 3&4-Testing the impact of pre-trip information on highway congestion

This impact was modeled by increasing coefficients for the commuting time coefficient in auto and in transit_drive_access utility function. The information about highway congestion was simulated by giving more negative weight to auto commuting time and by that, encouraging commuters to use public transit, what in reality would probably happened if the travelers are provided with that information. In Scenario 3 coefficient's absolute value was increased by 25% and in Scenario 4 that coefficient was increased by 50%. Values of the coefficients in those scenarios are shown in Table 35. Increasing coefficient, both for auto travel time from origin to destination and the coefficient for drive_access_to_transit may not be true, since that highway congestion stimulate commuters to use public transit. Also, it is true that highway congestion also creates problems accessing to park-and-ride facilities. In order to test the impact of this kind of pre-trip information, another sub-scenario was created (Scenario 3a and 4a) in which the highway congestion does not have impact on drive_access alternative. In these scenarios, just the coefficient for auto travel time has been increased.

Table 18. Auto Travel Time Coefficients

	Auto TT coefficient		
Scenario 3 & 3a	-0.0406	--->	-0.05075
Scenario 4 & 4a	-0.0406	--->	-0.06090

Scenarios 5&6-Testing the impact of pre-trip information on transit arrivals

Together with parking availability and highway congestion, uncertainty about transit arrivals makes commuters reluctant to use park-and-ride facilities and transit in general. If commuters are spared of that uncertainty, they will be more prone to use public transit. The way it will be represented in our model is by setting commuting time coefficient for transit travel time less negative. This will increase transit utility which was the purpose of the information. In Scenario 5, coefficient for transit travel time is multiplied by 0.75. In Scenario 6, the coefficient for transit travel time is multiplied by 0.5. The coefficients used for these scenarios are in Table 36.

Table 19. IVTT Coefficient

	IVTT coefficient		
Scenario 5	-0.0406	--->	-0.03045
Scenario 6	-0.0406	--->	-0.02030

In Scenarios 5 and 6 Transit Share grew to 10.72% and 12.25%, respectively. Transit increase was 15.10% and 31.53%. Number of park-and-ride users grew 15.52% in Scenario and 32.36% in Scenario 6.

Results

The main measures of effectiveness are park-and-ride share, transit share and total number of park-and-ride users in the network. That is obtained by running Mode Choice modulus in TransCAD and then analyzing the data. This analysis contains of exporting matrices for each mode into a table and performing a statistics analysis which gives a summation of total demand for each mode. When the total number of users for each mode is obtained, it is easy to find the mode splits. Some of the results are discussed in this chapter, but complete results are in the Appendix.

This model also provides us with the number of users for each park-and-ride facility. That is obtained by joining two tables from transit skims (origin-parking matrix and origin to origin parking matrix) and aggregating that table by park-and-ride nodes. The result is the total demand for each park-and-ride.

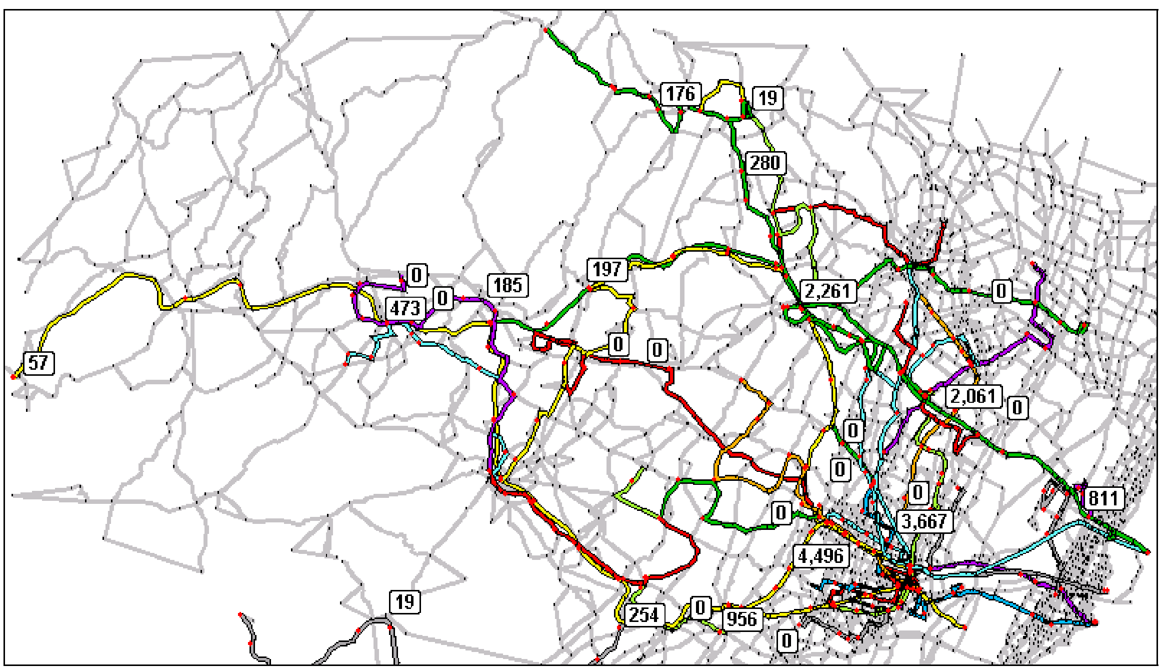

Figure 23. Total Demand for P&R facilities

These numbers are excessive, because of TransCAD limitation to restrict the capacity on the park-and-ride nodes. The effect of that limitation was reduced by decreasing capacity on the links going to park-and-rides and leaving just one access link to each facility open, but the negative effect could not be completely removed. This limitation creates more problems. For example, if there are three park-and-rides that are very close, the software will send all users to most favorable one, leaving the two neighboring ones empty, which in reality is not correct, but since the nodes do not have the capacity restrictions, this will happen (see Figure 48). Although, these numbers are excessive and possibly park-and-ride will never have this level of occupancy, but they are showing the potential users for park-and-ride facilities and give us the most favorable locations for park-and-ride facilities.

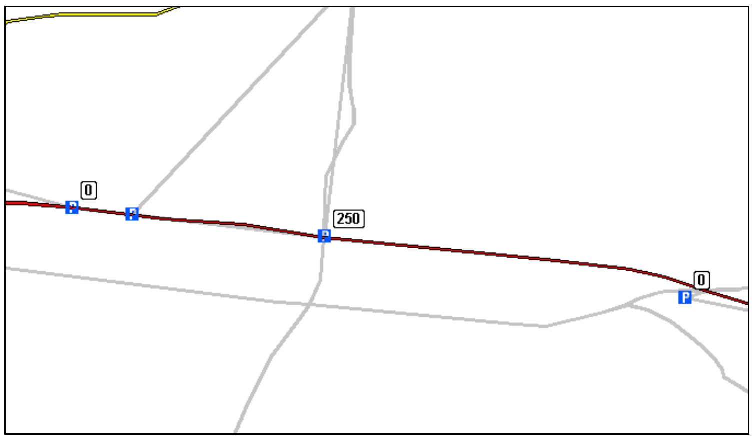

Figure 24. Sample estimated demand at P&R facility

Results Of Sensitivity Analysis

Transit Modal Split share increased 9.83% in Scenario 1 and 10.24% in Scenario 2 and their part in the modal split increased from 9.31% to 9.83% and 10.24 in Scenario 1 and Scenario 2, respectively. Number of park-and-ride users increased 7.86% in Scenario 1 and 14.20% in Scenario 2.

In Scenarios 3 and 4 the number of Transit users increased by 0.65% in Scenario 3 and 1.45% in Scenario 4, and the Transit share in the Modal Split was 9.37% in Scenario 3 and 9.45% in Scenario 4. Number of park-and-ride users decreased by 1.15% and 2.25% in Scenario 3 and 4, respectively. In Scenarios 3a and 4a park-and ride usage increased by 4.74% and 9.68%, respectively. In those scenarios Transit ridership increased by 4.61% and 9.39%.

In Scenarios 5 and 6 Transit Share grew to 10.72% and 12.25%, respectively. Transit increase was 15.10% and 31.53%. Number of park-and-ride users grew 15.52% in Scenario and 32.36% in Scenario 6. The results are depicted in Figure 49.

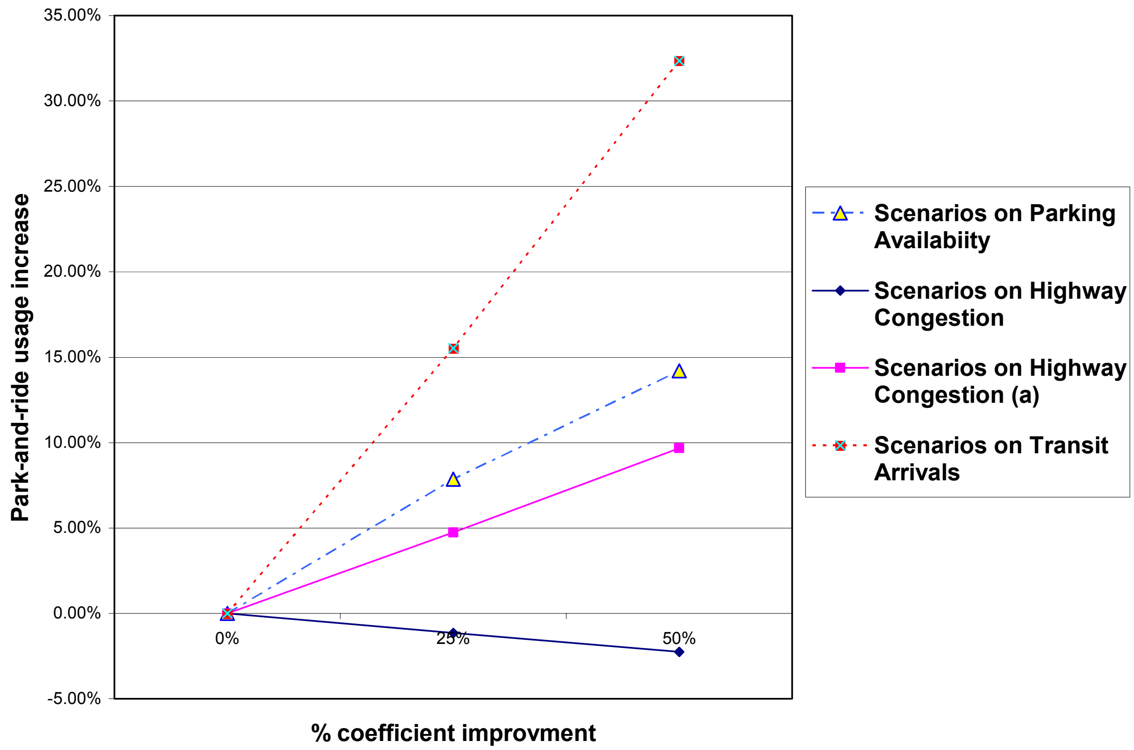

Figure 25. P&R increase in usage vs. % Coefficient improvement

Case Studies

In this section are described possible uses for the park-and-ride demand model through two case studies. First study shows the effect of changing location of park-and-ride facility and its implications on transit ridership and park-and-ride usage and the overall highway network. The second study examines the impact of merging several park-and-ride facilities into one through same categories.

Case study 1- Changing park-and-ride location

One of the potential use of this intermodal planning model is measuring the effect of changing the location of P&R facilities.

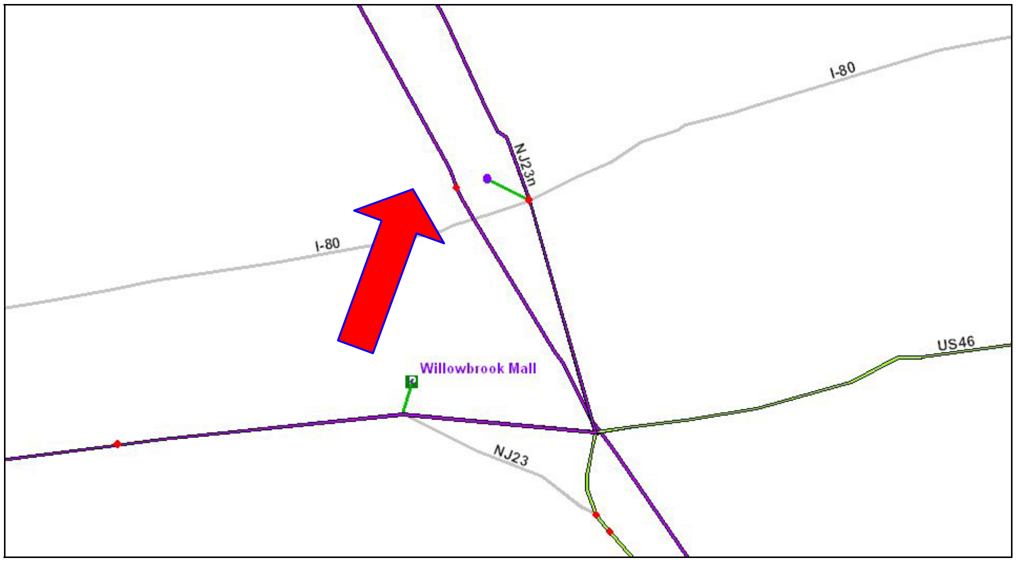

Figure 26. Evaluating the impact of changing the location of P&R facilities

The park-and-ride facility at Willowbrook Mall was moved further north on NJ Route 23.

The impact of this action was that there were 427 park-and-ride users lesser than on the Willowbrook Mall location or reduction of 3.9%. Total number of transit users dropped from 16828 to 16236 or 3.52% reduction. Total travel time on the network increased 31 hours. Total traveled miles on highway for auto users increased 3,784 miles. Average total travel time for park-and-ride users increased from 18.26 minutes to 18.53 minutes. This study shows that current position in Willowbrook Mall is more favorable then the location further north.

Case study 2- Changing park-and-ride location

Sometimes there is a need to evaluate a case when several intermodal facilities are consolidated into one, because of underutilization, cost cuts or any other reason. In this case study, twelve mostly underutilized park-and-ride facilities were merged into one (Dover Bus Terminal). Facilities are shown in Figure 51.

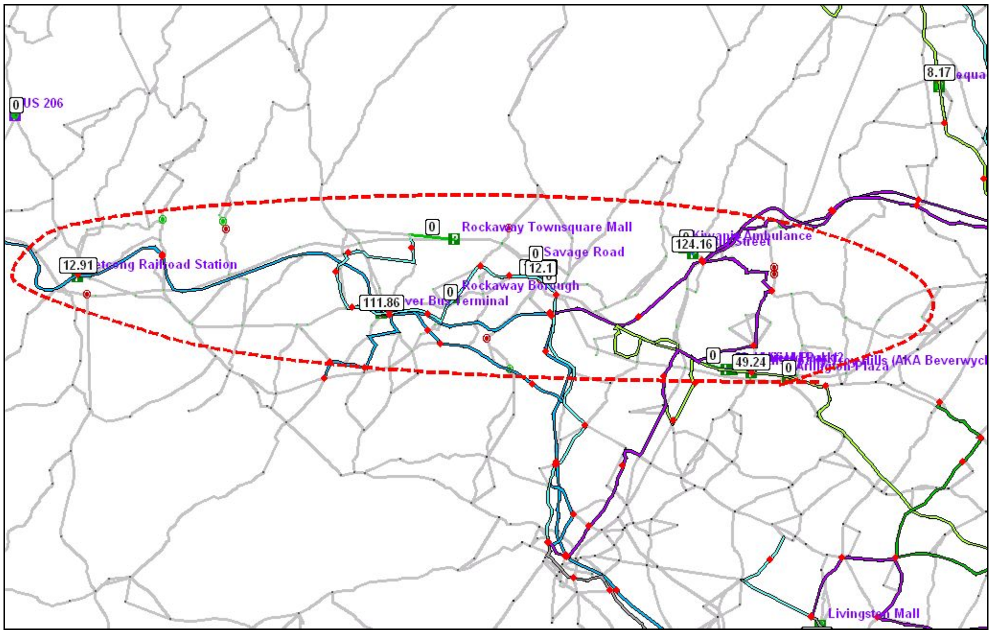

Figure 27. Sample Grouping of P&R facilities

The result of this would be reduced demand for park-and-ride facilities from 10,915 down to 10,442. Total travel time on highway network would increase for 64 hours and the total vehicle-miles would increase 3,961 miles. The average total commuting time for park-and-ride users across the network increased for from 18.26 minutes to 18.70 minutes. That increase in travel time is probably due to smaller number of options and commuters have to drive more to reach park-and ride facility that can be also further from their destinations then previous facilities. The effects of this action on the network were negative and according to the model results and considering only the travel time implications, the action would not be recommended. Table 37 summarizes presented results from case studies.

Table 20. Summary of Case Studies

Case Study	Number of commuters by mode			Transit Total	Average P&R commute time (min)	Total Travel Time on Network (hours)
	Auto	Intermodal	Pure Transit			
Base	776058	10915	5914	16828	18.26	115,793
Case 1	776619	10488	5779	16267	18.53	115,824
Case 2	776650	10442	5794	16236	18.70	115,857

As it can from the table, the more park-and-ride users we have, the lower is the total travel time on network. According to the model, the changes made reduced attractiveness of the park-and-ride facilities and diverted commuters to the highway mode and as a result of that total network travel time increased. Those results were not unexpected. By converting those travel time differences into monetary value, it can be seen what extra cost is imposed on commuters.

Again, it has to be mentioned that utility parameters were taken from literature and they are not really applicable here, so these case studies are for demonstration purposes only. For more applicable model, a market survey has to be conducted and actual parameters obtained.

Summary and Conclusions

In this report extensive literature review about impact of pre-trip information on commuters' travel pattern has been done. One of the models has been chosen and implemented into our intermodal network, which has been developed using TransCAD software. Results of modal split show significant increase in transit and park-and-ride usage as an impact of having the accurate information before the trip has been started. Those results are based on the model that was calibrated for other survey so it is not quite applicable here, but what it is shown here is that an intermodal network modeling can be developed which can account for the impact of pre-trip information on intermodal network. This fact makes that model different from the existing models that are mainly focused just on the highway networks. More accurate planning model has to be calibrated on the results of a survey. Furthermore, the operational tools may be developed.

<u>The work that has been presented in the previous sections may be summarized as follows:</u>

- A thorough literature review on models describing the impact of information on driver's decisions has been presented

- Four major groups of models have been presented: models with pre-trip information, models with en-route information, models with transit information and models describing impact of parking information

- A model that describes usage of park-and-ride system and which should help reduce highway congestion was chosen, adjusted and implemented in our study

- An inter-modal network model including highways, bus and rail routes and park-and-ride facilities has been created using data from NJTPA, NJ Transit and Tiger data

- An Origin-Destination Matrix for the above network, based on data from the NJTPA model, has been developed

- The model has been calibrated by adjusting the coefficients so that the total park-and-ride demand from the model fits the total real usage of the park-and-rides

- The impact of various types of information to travel patterns has been modeled properly adjusting the value of the parameters in the model

- Possible usage of this decision tool has been described through a couple of hypothetical scenarios and by observing the effect of the decisions made

The model has the capability to analyze travel patterns in an inter-modal network including park-and-ride facilities. The model estimates changes in the network travel patterns that result from different information provided to travelers, alternative pricing and operating policies, changes in transit and park-and-ride systems and future increase in travel demand.

Recommendations

- Perform a market survey in order to obtain real data and calibrate the model. This is necessary because the preferences of the travelers in a specific corridor need to be obtained for every model. Those data would be statistically analyzed and parameters would be estimated accordingly.

- A dynamic model can be developed which would be more accurate and more suitable for real time implementation. The network should be modified and implemented in VISTA, which has dynamic capabilities, necessary for implementing a dynamic model.

- The model could be interfaced with existing state and regional planning tools and provide the capability of inter-modal network analysis, evaluation of park-and-ride pricing policies and operation schemes, the impact of information on traveler’s decision and its effect on the network patterns.

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