Mobility considerations in restricting choice sets in modal choice models

Frank Primerano
BSc(Ma&CompSc)(Hons)
PhD Student

Ph: (08) 8302 1864
Fax: (08) 8302 1880
Email: Frank.Primerano@unisa.edu.au
http://www.unisa.edu.au/tsc/index.html

TSC
Transport
Systems
Centre

University of South Australia

25th Conference of Australian Institutes of Transport Research (CAITR03)
hosted by the
Transport Research Centre
University of South Australia

3 – 5 December 2003

1 Introduction

Modal choice models are used to estimate the choices individuals make given the mode alternatives available to them. To better estimate the modal choice of an individual, attempts have been made to eliminate mode alternatives from an individuals choice set that are considered to be unavailable based on their personal and household characteristics. Commonly, the membership of private car related modal choices in these modal choice sets are questioned and usually based on whether the individual has a driver's licence and whether the household they are a member of own any vehicles.

By further processing data already available from revealed preference surveys, this paper will discuss research that attempts to derive the movements of household vehicles and household members with driver's licences in space and time to determine the mobility of each individual at any moment. Essentially, this procedure will determine whether an individual with a driver's licence has a vehicle to use when and where they need it. In addition, the ownership of children and adult bikes within the household will be considered for bike related trips.

The results from the application of this procedure on several modal choice models are discussed. This paper then concludes with a discussion on how this procedure can be further improved to better estimate mode choice alternatives available to an individual and also other potential applications of this procedure.

2 Choice sets

2.1 Modal choice models

Given the mode alternatives available to an individual, modal choice models based on random utility theory aim to determine the probability of an individual choosing to use an alternative above all the others. There are discrete choice modelling packages available such as Limdep that allow the analyst to specify different choice sets between observations. The ability to vary the number of alternatives available between observations not only allows the representation of the difference between alternative choice sets between individuals to occur but can also represent how the choice set can vary for an individual over time.

In many studies, an individuals mobility for private vehicles depended on whether they had a car driver's licence and the ownership of vehicles by the household. These can be used to restrict the choice set directly. Bowman (1995) developed a tour destination and mode choice model where the choice: to drive alone was included in the choice set if the person had a driver's licence and the household of the individual had at least one vehicle; and transit alternatives where available based on the transit connectivity between the origin and destination zones. Similarly, Ben-Akiva and Lerman (1985) described a trinomial mode choice model for work based trips where:

the drive alone option was restricted by the individual having a driver's licence and the household having a vehicle; and transit bus was based on the individual residing and working within a half mile of a transit stop. Holyoak (2001) developed a mode choice modal to estimate the modal split of travel in metropolitan Adelaide. The choice sets for all observations remained the same, however mobility related attributes such as the number of household cars and bikes and the type of driver's licence held by the individual where also considered in the deterministic component of the utility function. It was found that the type of driver's licence held was not significant in the models developed (Holyoak, 2001). Ben-Akiva and Lerman (1985) describe a system of models (based on work by Ruiter and Ben-Akiva (1978)) used to model all aspects of urban passenger travel in San Francisco. Part of this system models auto ownership to influence the mode choice of primary workers in households and includes the number of automobiles remaining in the influence of mode choice for other non-work activities (Ben-Akiva and Lerman, 1985).

2.2 Generation of choice sets

Many choice models assume a pre-specified universal choice set applies to all individuals. Models making such assumptions can be incorrectly specified leading to inconsistencies in parameter estimations (Ben-Akiva and Boccara, 1995, Cascetta and Papola, 2001). It is further argued that although alternatives may be available to an individual, this does not necessarily mean that all available alternatives are considered (Horowitz and Louviere, 1995). It has been reported that assuming that a number of choices are available for an individual when only one alternative is actually available leads to the following problems (Swait, 2001):

- the alternative specific constant for the available alternative is downward biased;
- the effects of attributes on alternatives become diluted with the presence of alternatives irrelevant to the individual.

The majority of research into modelling choice set generation has used the two-stage process of making a choice developed by Manski (1977) given by

$$P_n(i) = \sum_{C \in G_n} P_n(i \mid C) P_n(C) \qquad \textbf{Equation 1}$$

which means that the probability of individual n choosing alternative i is the summation over all possible choice sets G_n for the individual of the probability of choosing i given the choice set of available alternatives multiplied by the probability of choice set C being considered by the individual.

The model in Equation 1 is used to modify existing models based on random utility theory, with the inclusion of a term that represents the availability of an alternative. In discrete choice models, an alternative is either available or is not available. With the inclusion of this term, alternatives can vary in the degree of availability (Cascetta and Papola, 2001).

Since the only information obtained from revealed preference survey data are on the alternative chosen, the attributes reflecting the availability of an alternative are based on stated preference surveys where individuals are asked about alternatives not chosen (Ben-Akiva and Boccara, 1995). Stated preference surveys collect choice responses by individuals within hypothetical markets (Louviere et al, 2000). The advantage of supplementing revealed preference data with stated preference data is that individuals can be asked about:

- the alternatives they actually have available to them;
- what alternatives they would or would not consider;
- why they would or would not consider an alternative;
- what alternatives do they not know about;
- both qualitative and quantitative attributes that affect their choice set; and
- how would an individual's choice change if they were given an alternative that they previously did not have?

Horowitz and Louviere (1995) argued that standard operational consideration sets are indicators of preferences providing no additional information for predicting choices beyond what is already contained within the utility function. They conclude that the two-stage process of Manski (1977) is not necessary to model choice where information about the consideration set can be used to improve the specification of choice models. Along similar lines (although still adopting the Manski model) Swait (2001) developed a new model of choice set generation where the choice set probabilities were taste driven rather than using exogenous information.

2.3 Using existing information

Following the review of modal choice models, there appears to be two ways in which the mobility of an individual can be incorporated in these models:

1. by the inclusion of variables that influence the choice an individual makes; or
2. by determining the alternatives available to an individual and restricting the choice set to these available alternatives.

The inclusion of variables to influence an individual's choice can be made in two ways. One method is to directly indicate the mobility of an individual through the inclusion of variables that give an indication of mobility. Alternatively, a system of equations can be developed where components of the system model characteristics of mobility such as car ownership and incorporate these models into modal choice models via inclusive values.

The advantage of including variables of mobility within the modal choice model is that these models will have an influence on the choice set without having to determine the choice set. For example, if the mobility variable inversely influences an alternative then for that observation one would hope that the mobility variable would reduce the probability of choosing that alternative to the point where it becomes insignificant. The disadvantage of this method is that the mobility variable will compete with the market share of alternatives and other attributes that may influence the mode choices far greater than the mobility variables themselves. There can be situations that the mobility related variables can become insignificant in the models.

The advantage of determining the choice set of individuals is that the choice set represents all the alternatives available to an individual and does not include those alternatives that are not available, which can skew the modelled results. The disadvantage of this method is that it is difficult to determine the actual choice set that was available to an individual at a particular point in time.

The research devoted to developing models of choice set generation is still growing. Most choice set generation models adopt the Manski model however, care should be taken not to merely replicate the choice probabilities and calling these a degree of availability of alternatives. This can be avoided through the use of stated preference data however further research is required to improve these choice set generation models.

The purpose of this paper is to develop a method to get closer to the set of actual mode alternatives available to an individual for improved estimation of modal choice models. It is believed that there is a rich source of information not properly utilised within revealed preference survey data that can identify the alternatives available to individuals.

Revealed preference survey data contains information on the choices made by individuals within a household. There are two vital pieces of information that can be drawn from these surveys:

1. the resources, mobility wise, that are available to the individuals within the household (ie number of vehicles, driver's licence holders); and
2. the period of the survey where resources are being used by individuals and how they are being used.

Since this information can be extracted, it should be possible to estimate with confidence the movements of these resources. In other words, it is possible to determine when and where vehicles and household members are at any time during the survey. With this information, it can be determined whether individuals have those vehicles available to them when they need them.

By approaching the real choice set of available alternatives, this research should complement the methods discussed above by eliminating alternatives that are irrelevant to the individual at that point in time. By incorporating the mobility procedure, these choice generation models can focus on determine the degrees of availability or consideration of alternatives that are possible for the individual to choose.

3 The procedure for determining vehicle mobility

3.1 1999 Metropolitan Adelaide Household Travel Survey

The data used to develop the models were collected from the 1999 Metropolitan Adelaide Household Travel Survey (MAHTS99). MAHTS99 was conducted by Transport SA to gather information on the population's travel behaviour for the purpose of planning Adelaide's transport needs (Transport SA, 1999).

The survey gathered information based around people's day-to-day activities over two consecutive days within the Adelaide Statistical Division. A sample of approximately

9,000 homes, representing 2% of all private dwellings, was randomly selected. The final information gathered included:

- *Household information* including household type, household members and vehicles and bicycles available;
- *Personal information* on each household member including occupation, location of occupation activities, work related information, disabilities, personal income and attitudes towards public transport; and
- *Travel information* including where, when, how, why and cost of travel.

3.2 The algorithm

This section describes the algorithm developed on which the procedure to estimate the mobility of individuals was based upon.

In order to develop the mobility variable, a table was constructed that identifies all the stops made by every vehicle in all households. The table contains the following fields:

- Household ID;
- Vehicle ID;
- Driver;
- Day;
- Vehicle stop ID;
- Start time;
- End time;
- Origin zone;
- Destination zone.

The stops travelled by vehicles are all in sequential order according to time and space. In some cases, the number of vehicles declared as owned or used by the household was less than what was considered as actually being used by the household. In these circumstances, it was assumed that the household had access to another vehicle and this was added to the list of available vehicles.

The vehicle table is constructed by reading all stops where the mode is *car as driver* (as defined in MAHTS99). All the stops already entered in the vehicle stop table are scanned to determine the appropriate location of the record for the current stop. This is completed by ensuring that:

- the end time of the previous stop is less than or equal to the start time of the current stop;
- the end time of the current stop is less than or equal to the start time of the next stop;
- the origin zone of the current stop equals the destination of the previous stop;
- the destination zone of the current stop equals the origin zone of the next stop.

If there is no suitable position for the current record stop for this vehicle, the stop records for the next vehicle are searched using the same procedure as above. If no suitable position is found for the current stop record for all vehicles, and an extra vehicle has not been added, then a new vehicle will be added. Note that a new vehicle will only be added once. Beyond this, it is assumed an error has occurred and the current record stop will be omitted.

The next phase of this algorithm was to use the vehicle stop table created to determine if a car was available for each trip. Note that trips differ to stops in that a trip is made up of a number of stops. This part of the algorithm determines which trips could have been made where the individual could have driven the vehicle. Hence, it was considered that if the trip was made by mode *car as driver*, this automatically means that the individual had access to a vehicle (since they actually drove a vehicle). For all other modes, however, it was determined whether a vehicle was available from the vehicle stop table and that the person involved with the trip had a driver's licence.

The availability of a vehicle for a trip was determined by searching through all the stops made by each vehicle within the appropriate household to determine whether a trip or a number of consecutive trips could be performed while the vehicle was not in use. A vehicle was available for use by an individual for a specific trip or number of trips based on one of three criteria:

1. The start and end time for a trip or a group of consecutive trips was less than the start time for the first vehicle stop AND the destination zone of the last trip within the group of consecutive trips was equal to the origin zone of the first stop for that vehicle;
2. The start time of the first trip within the group of consecutive trips was greater than or equal to the end time of a vehicle stop and the origin zone and destination zone, respectively were equal AND the end time of the last trip within the group of consecutive trips was less than or equal to the start time of the next vehicle stop and the destination and origin zones, respectively are equal.
3. The start time of the first trip within the group of consecutive trip is greater than or equal to the end time of the last trip the vehicle travels AND the destination and origin zones respectively are equal.

To summarise, if the car is at a location and a time when an individual needs the vehicle AND it can be returned in time and at the location where the next person can use it, then the car is considered to be available to the individual, given they have a driver's licence. It should be noted that in some instances a mode would be registered as 'car driver' yet the driver had no indication of a driver's licence. In these situations, it was assumed that the individual had a car licence and so whenever a trip involved an individual without a driver's licence, a search would be performed to see if they had driven a car.

4 Application

The mobility variable was derived to determine whether an individual was able to use specific mode alternatives at the time they made a trip. The mobility variable was developed for three of the mode alternatives; *drive alone*, *drive passenger,* and *bike*. The resultant variable was then used to determine the choice set of available modal choices for each observation.

Determining whether an individual had access to a bicycle was simply determined by the number of children and adult bicycles in the household. If the individual was considered as being *preschool* (ie. too young to attend school) then their access to a bike depended on the household having children's bicycles. For full-time students it depended on whether they had either children or adult bicycles. For the remaining individuals (representing adults) their access to a bicycle depended on the number of adult bicycles owned by their household.

4.1 The modal choice models

The models developed were nested logit models with eight alternatives as described in Table 1. The alternatives were divided into a two-level nested logit tree structure where non-motorised alternatives included walk and bike and motorised modes incorporated the remaining alternatives.

Table 1 The modal choice alternatives and their description

Mode	Description
Drive Alone (DA)	Drove the entire trip alone
Drive Passenger (DP)	Drove with passengers during part or all of trip
Car Passenger (CP)	Passenger in a car with driver a member of household
Ride Share (RS)	Passenger in car with driver from another household
Walk (W)	Walk and wheelchair trips
Bike (B)	Bicycle
Public Transport (PT)	Includes buses, trains, and tram
Taxi (T)	Includes standard taxi, access taxi and hire cars

The modal choice models were developed for three activity types, namely personal business, shopping, and social and recreation activities. Personal business/service related stops were those that involved transacting personal business or obtaining a service where no goods were involved. Social and recreation related travel involved visiting someone, active and passive participation in sporting activities; and all entertainment activities. Travel for shopping was when an individual entered a shop (any premises which sells goods) irrespective of whether a purchase was made (Transport SA, 1999).

The figures in Table 2 show the modal split for home-based travel for the three activity types. The private car was by far the mode used the most for travel. Vehicle drivers whether alone for all or part of the trip were the highest of all modes. Car passenger travel was the highest for personal business as individuals such as children who undertake a lot of personal business make many of these trips. Other modes were also significantly represented, in particular trips made by walking.

Table 2 The modal split for each home-based activity type from MAHTS99

Mode	Personal Business	Shopping	Social Recreation
Drive Alone	30.4%	44.3%	30.8%
Drive Passenger	18.6%	20.4%	17.2%
Car Passenger	32.9%	13.1%	22.7%
Ride Share	7.2%	5.1%	10.5%
Walk	8.5%	12.2%	14.7%
Bike	0.3%	0.8%	1.7%
Public Transport	1.6%	3.7%	1.7%
Taxi	0.5%	0.4%	0.7%

4.2 Discrete choice modelling

This section is intended to provide the reader with background knowledge of discrete choice modelling so that a better appreciation can be obtained for the results obtained from this research.

The simplistic form of the utility function is:

$$U_{in} = V_{in} + \varepsilon_{in} \qquad \textbf{Equation 2}$$

where U_{in} is the utility of alternative i for individual n
V_{in} is the deterministic component (or representative components)
ε_{in} is the disturbances (or random component).

The deterministic component can be specified as

$$V_{in} = V(\mathbf{x}_{in}) = \beta_1 x_{in1} + \beta_2 x_{in2} + \beta_3 x_{in3} + \ldots + \beta_K x_{inK} \qquad \textbf{Equation 3}$$

where $\mathbf{x}_{in}$ is the vector of attributes of alternative i for individual n and the β's are the unknown parameters (coefficients).

The β coefficients of the variables in the deterministic component are estimated using the maximum likelihood method. The log-likelihood function has the form

$$LL(\beta) = \sum_{n=1}^{N} \frac{\ln P_n(\beta)}{N} \qquad \textbf{Equation 4}$$

where $P_n(\beta)$ is the probability of an outcome occurring for an individual n, N is the sample size and β is the vector of coefficients that need to be estimated. The idea is to find a set of β coefficients that will maximise the log-likelihood, hence a lot of the methods focus on trying to find a new set of β that will get the log-likelihood closer to its maximum (Train, 2002).

A measure of goodness-of fit called the likelihood ratio index, which is similar to R^2 in regression and will stay the same or improve when variables are added. Calculating the likelihood ratio between the current model specification and a model without coefficients provides the following likelihood ratio index

$$\rho^2 = 1 - \frac{\max LL(\hat{\beta}_c)}{\max LL(0)} \qquad \textbf{Equation 5}$$

The likelihood ratio index in Equation 5 can be further improved to allow for comparison with other models by adjusting ρ^2 for degrees of freedom gives the correct ρ^2

$$\bar{\rho}^2 = 1 - \frac{\max LL(\hat{\beta}_c)}{\sum_{i=1}^{N}(J_i - 1) - K} \Bigg/ \frac{\max LL(0)}{\sum_{i=1}^{N}(J_i - 1)} \qquad \textbf{Equation 6}$$

where J_i is the number of alternatives available to an individual and K is the total number of variables in the model. The corrected version of the likelihood ratio index is useful for testing whether the addition of variables make an impact on the model (Louviere et al, 2000).

5 Results

A total of nine models were created where for each of the three activity types, three models were developed where:

- the choice set for all observations remained the same (normal);
- drive alone and drive passenger were in the choice set if the individual had a driver's licence (car licence);
- the mobility procedure was used to determine the inclusion of drive alone and drive passenger in the choice set and also the inclusion of bike based on bicycle ownership of the household (mobility).

The log-likelihood and the goodness-of-fit measures for each model are shown in Table 3. Judging from the large goodness-of-fit values, all the models appear to have been well estimated. The improvement in goodness-of-fit values from the 'normal' models to the 'car licence' models were 1.2% for social and recreation trips, 3.1% for shopping trips, and 4.4% for personal business trips. The goodness-of-fit values improved dramatically for the 'mobility' models from the 'normal' models with 14.5% improvement for shopping trips, 16.7% for personal business trips, and 19.0% for social and recreation trips.

Table 3 Log-likelihood and adjusted rho squared values from modal choice models for various home-based activities and alternative choice set restricting procedures.

	Normal		Car Licence		Mobility	
Activity	LL	Adj Rho	LL	Adj Rho	LL	Adj Rho
Personal Business	-13154	0.617	-12227	0.644	-9614	0.720
Shopping	-8336	0.744	-7593	0.767	-4817	0.852
Social/Recreation	-16491	0.669	-16082	0.677	-10150	0.796

The alternative specific constants (ASCs) were also analysed to determine if any significant changes occurred. The ASCs represent the mean of the distribution of unobserved effects. The significance of the ASCs provides an indication of the influence of the random components across the sample. Statistically significant ASCs mean that the observed components of a model captured the major sources of variability (Louviere et al, 2000). The referent alternative for the motorised nest was drive alone and for the non-motorised nest, the walk alternative. The results in Table 4 show an overall increase in the size of the coefficients for each ASC from the normal model compared with the mobility model (with the exception of drive passenger for personal business trips and bike for shopping and social/recreation trips). These results are expected since it was found by Swait (2001) that for a chosen alternative, the inclusion of alternatives not considered by the individual would cause a downward bias in the chosen alternative's ASC. Applying this to the results in Table 4, all the ASC's of alternatives that have increased are those alternatives that are always available. So at times when these alternatives are chosen, in the 'normal' case and some times for the 'driver's licence' models, these observations will include alternatives that are not necessarily available. The only two alternatives where their corresponding ASCs did not increase for all models were drive passenger and bike, the two modes that could be included or excluded from the choice set, hence they never have unavailable alternatives.

Table 4 Estimates of the coefficients (and associated t-statistics) for the alternative specific constants for all modal choice models

		Normal		Driver's licence		Mobility	
Activity	Variable	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Personal Business	Drive Passenger (DP)	-1.85	-11.18	-0.65	-9.23	-0.59	-8.24
	Car Passenger (CP)	-1.11	-10.24	-2.99	-24.69	-6.24	-23.44
	Ride Share (RS)	1.09	9.35	-0.75	-5.73	-3.43	-12.80
	Bike (B)	-4.87	-12.21	-2.62	-13.09	-5.32	-14.15
	Public Transport (PT)	-0.71	**-1.75**	0.02	**0.09**	-2.86	-8.03
	Taxi (T)	0.76	3.56	-1.16	-6.85	-3.91	-14.48
Social Recreation	Drive Passenger (DP)	-11.34	-75.12	-11.41	-74.27	-12.96	-49.61
	Car Passenger (CP)	-4.95	-28.03	-9.58	-40.96	-7.63	-29.95
	Ride Share (RS)	3.70	32.18	-0.47	-2.65	-3.23	-15.27
	Bike (B)	-3.72	-26.18	-3.73	-27.17	-3.34	-19.08
	Public Transport (PT)	-4.38	-15.48	-7.96	-26.12	-9.64	-32.13
	Taxi (T)	-0.24	**-0.87**	-0.44	**-1.58**	-3.18	-8.82
Shopping	Drive Passenger (DP)	-15.22	-42.55	-17.13	-36.76	-17.41	-31.06
	Car Passenger (CP)	-13.68	-40.44	-16.46	-36.18	-16.08	-23.14
	Ride Share (RS)	-6.09	-20.03	-8.91	-21.09	-10.93	-15.91
	Bike (B)	-2.84	-15.15	-2.75	-15.43	-2.35	-10.85
	Public Transport (PT)	-7.24	-18.85	-10.30	-21.47	-13.09	-17.93
	Taxi (T)	-5.03	-10.59	-5.91	-11.24	-7.46	-9.25

The t-statistic for public transport and taxi (both with low market share for all activities) improved significantly for social/recreation and personal business trips. In particular public transport for personal business trips and taxi for social/recreation trips were insignificant (< 1.96) for the normal and car licence models (t-statistics in bold in Table 4), which indicate that the models did not capture the major sources of variability. The public transport and taxi modes in the mobility models on the other hand have significant ASCs, providing an improved and reliable estimate of choice for these modes.

6 Summary and Conclusion

This paper has investigated the issue of choice set generation for modal choice models to reflect the mobility of an individual at a specific time. Using the revealed preference data already used for developing the modal choice models, a procedure was created to determine the mobility of individuals with driver's licences. This procedure is unique because it considers the availability of household vehicles when they are required by the individual rather than assuming the vehicles are always available. The procedure also considered bicycle ownership for children and adults within a household.

The procedure was then tested on modal choice models for personal business, social/recreation, and shopping activities. The procedure was compared to models where the choice set was the same for all individuals all of the time and also with models where the individual having a driver's licence was considered. Given the models were already well estimated for the normal case, to get further improvements of such magnitude for the models based on the mobility procedure shows the benefit of spending time to define appropriate choice sets for each observation. The results also showed that a downward biased in the ASC's of alternatives available occurred when alternatives irrelevant to the individual were included in the choice set, as discussed by Swait (2001). Furthermore, some of the modal choices least chosen were represented significantly once unavailable modes with a large market share were filtered out.

The field of choice set generation was further investigated. By approaching the real choice set of available alternatives, the procedure developed in this paper should complement the choice set generation methods by eliminating alternatives that are irrelevant to the individual at that point in time. By incorporating the mobility procedure, these choice generation models can focus on determine the degrees of availability or consideration of alternatives that are possible for the individual to choose.

In short, there is a significant amount of information present in revealed preference survey data that may be used to determine the alternatives available to individuals. More processing of survey data can reveal a wealth of information that can be used to refine and improve the efficiency and reliability of behavioural models. This can allow stated preference surveys to be designed to focus on collecting information that are impossible to obtain from revealed preference survey data.

7 Further research

The mobility procedure was only applied to alternatives related to driving a vehicle. From revealed preference survey data it could also be possible to determine whether being a car passenger is possible by determining whether both a household member with a driver's licence and a vehicle are both at the same location and at the same time as the individual who wishes to undertake travel.

The procedure could also be expanded to consider the availability of public transport. In determining the availability of public transport both Bowman (1995) and Ben-Akiva and Lerman (1985) considered public transport connectivity at origin and destinations of trips. Such a procedure could also be applied to remote urban and rural areas to determine whether alternatives such as public transport are available when individuals require it. From a planning perspective this idea could be expanded and used to better serve individuals who have restricted choice sets with alternatives such as public transport. The mode alternatives available to an individual could give an indication of social exclusion/inclusion, allowing policy makers to create policies to improve or create alternatives.

Another possible application of such a procedure could be in the development of ride share schemes at the work place. This can be done by analysing trip patterns of workers and matching the appropriate employees for ride sharing based on location of employees' homes and timing of trips to and from work.

Reference

Ben-Akiva, M. and Boccara, B. (1995). Discrete choice models with latent choice sets. *International Journal of Research in Marketing,* **12,** 9-24.

Ben-Akiva, M. E. and Lerman, S. R. (1985) *Discrete Choice Analysis: Theory and Application to Travel Demand,* MIT Press, Cambridge, Massachusetts.

Bowman, J. L. (1995). Activity based travel demand model system with daily activity schedules. Masters Thesis, *Department of Civil and Environmental Engineering,* Massachusetts Institute of Technology, USA.

Cascetta, E. and Papola, A. (2001). Random utility models with implicit availability/perception of choice alternatives for the simulation of travel demand. *Transportation Research Part C,* **9,** 249-263.

Holyoak, N. M. (2001). The formulation and development of a policy sensitive analysis tool for the evaluation of travel demand management measures. PhD Thesis, *School of Geoinformatics, Planning and Building,* University of South Australia, Adelaide.

Horowitz, J. L. and Louviere, J. J. (1995). What is the role of consideration sets in choice modelling? *International Journal of Research in Marketing,* **12,** 39-54.

Louviere, J. J., Hensher, D. A. and Swait, J. D. (2000) *Stated Choice Methods - Analysis and Application,* Cambridge University Press, Cambridge.

Manski, C. (1977). The structure of random utility models. *Theory and Decision,* **8,** 229-254.

Ruiter, E. and Ben-Akiva, M. E. (1978). Disaggregate travel demand models for the San Francisco area: system structure, component models and application procedures. *Transportation Research Record***,** 121-128.

Swait, J. (2001). Choice set generation within the generalized extreme value family of discrete choice models. *Transportation Research Part B,* **35,** 643-666.

Train, K. (2002) *Discrete Choice Methods with Simulation,* Cambridge University Press (Not yet published).

Transport SA (1999). 1999 Metropolitan Adelaide Household Travel Survey - Interviewer's Manual. Government of South Australia, March.