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SOME IMPROVEMENTS TO CURRENT PRACTICES OF ESTIMATING INDIVIDUAL TRAVEL CHOICE MODELS WITH EXISTING DATA

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Abstract:

Much money has been spent on the collection of comprehensive household travel (HIS-home interview survey) data in Australian cities which has in turn been used, and will continue to be used in the foreseeable future, for the estimation of travel demand models by transport planning authorities. The proliferation of multinomial logit (MNL) and other estimation/application packages also means that individual travel choice models will continue to be prominent. In this event it is worth ensuring that maximum value is obtained. Improvements to current individual travel choice modelling may be achieved in at least three aspects:- First, if the Lancastrian paradigm of consumer behaviour is strictly followed and only characteristics of the transport system are included in the utility function, but the influence of different individual attributes is allowed for by appropriate market segmentation. Second, if the unit of analysis adopted is the journey (i.e. the round trip from home back to home) and not the trip. Third, if choice sets are carefully selected, which in the case of the MNL model could result in a hierarchical decision process for the journey-to-work modal choice. The Ballarat HIS data was used for the exercise and resulted in following current practices. Furthermore, the differential impact of each LOS variable on different socio-economic segments could be detected.

INTRODUCTION

Disaggregate, behavioural or individual choice modelling of travel behaviour has very much become the quantitative transport planning tool of recent and near future years. Whether or not it deserves to replace aggregate modelling of travel behaviour is not the preserve of this paper. One particular form of individual choice model (ICM) appears to be favoured over other contenders for pragmatic rather than theoretical reasons. This model is commonly known as the multi-nomial logit (MNL) model - its precise multinomial logit (MNL) mathematical form is given later in the paper. Further, transport planning authorities tend to use existing metropolitan-wide data, i.e. home interview survey (HIS) data, as extra data collection is expensive and not necessarily any more useful for the estimation of MNL models of travel behaviour.

It is assumed that the reader is reasonably familiar with the theory and application of the MNL model to travel behaviour. The authors take the view that whilst the current situation may or may not be an ideal one, given the current knowledge of travel behaviour and travel behaviour modelling, some effort should be made to maximise the usefulness of MNL models of travel behaviour using the commonly available MNL estimating/application packages and existing (i.e. HIS) data sources.

With the above context in mind, the paper is structured in the following manner. First, the limitations of the MNL model are discussed briefly. Second, the shortcomings of current applications as perceived by the authors are discussed irrespective of whether these perceived shortcomings stem from the limitations themselves or from poor practices. Third, but actually in conjunction with the second stage, methods to overcome these shortcomings are suggested and finally the results of putting these methods into practice using the 1970 HIS data from Ballarat (Vic.) are presented and reviewed.

THEORETICAL CONSTRAINTS ON THE MNL MODEL

Independence from Irrelevant Alternatives (IIA) Property

The reader will undoubtedly be aware of the notorious independence from irrelevant alternatives (IIA) property. This property or axiom about selection probabilities simply states that the relative odds of one alternative being chosen over a second should be independent of the presence or absence of other unchosen alternatives (McFadden 1974). To understand why this is a restriction it is necessary to define the assumptions that underly the MNL model.

Random utility theory (McFadden 1974, Williams 1977) postulates that an individual has a utility function that can be written in the form:

$$U = V(x) + \varepsilon(x) \tag{1}$$

where U is the utility,
- V is constant and represents the average value of utility placed on that alternative by the individual,
- ε is stochastic and reflects the variability in utility attached to that alternative by the individual

and
- x is the set of attributes associated with that alternative.

Once $V(x)$ and $\varepsilon(x)$ for the competing alternatives have been 'calculated' by an individual the choice he then makes is always the one that maximises his utility.

The MNL model can be derived from eqn (1) by assuming that $\varepsilon(x)$ is independently and identically distributed (with respect to each alternative) with the Weibull distribution (McFadden 1974, Daly 1979). It is this assumption that really causes the trouble as it basically means that each alternative in the choice set (as assumed by the modeller), is assumed to be equally different. This requirement leads to the classic red bus/blue bus conundrum, whereby the introduction of a new bus line different only by colour (red), to an existing two mode competition between blue bus and private car, each having 50 per cent, would lead to a MNL model predicting an unrealistic modal split of one third to each mode. However, as will be shown later in the paper, this apparent shortcoming can be overcome, ironically enough, by judicious use of the IIA property itself.

Choice Set Specification or Identification of Relevant Alternatives

The red bus/blue bus conundrum introduced immediately above serves to illustrate the problems of specifying the appropriate choice set. Bias can obviously creep in if people are included in say a binary model of modal choice (i.e. private car vs public transport) when one of those choices is not really available to them (or more precisely, when they do not consider it to be available to them). The specification of choice sets is an area where the need for further research has been well recognised (see Morris 1979).

The Linear Additive Utility Specification

For the purposes of current estimation packages, it is necessary to assume that the utility function is linear (in the parameters, not necessarily in the variables themselves) so that the contribution made to the overall utility by each attribute is added to that made by each other attribute (see eqn (2) below). The reasons for this are dealt with later in the section on consumer behaviour. The additive view specifically allows trade-offs between attributes. An individual can be exactly 'compensated' for a reduction in the level of one attribute by some increase in the level of another. This compensatory view of travel choice behaviour is not necessarily the 'correct' one; it is possible to formulate non-compensatory theories of travel choice behaviour (see Richardson 1979; Recker and Golob 1979).

Degree of Disaggregation

Equation (1) was certainly formulated at the individual level. However, it is always estimated using data collected about many individuals - McFadden (1974) does not even bother to specify eqn(1) at the level of the individual, preferring to go straight to a group of individuals so that $V(x)$ represents the group average utility and the individual variations within that group. It is very rare that more than one observation (for the same choice) is available per individual in the data set. This is simply because travel surveys have always concentrated on manifest travel behaviour - the modelling approach has been one of revealed preference. Functional analysis offers a truly individual approach, but is not elaborated upon here; one reason being that a new survey, albeit small, is required each time a new question is to be addressed (see Louviere 1979).

THEORETICAL UNDERPINNINGS OF MNL MODELLING PRACTICE

Predictive Tasks Suitable for MNL Modelling

Any limitations in the current use of MNL models can only be discussed in the context of what the modeller is trying to achieve with them. Broadly speaking, the modeller is attempting to predict travel behaviour at some time in the future, be it tomorrow or the year 2001. The type of forecasting that the authors think the MNL model is particularly suited to is that of short term, or policy, analysis. That is, MNL models may be appropriate to provide guidance on the likely result of say, increasing public transport fares by 20 per cent, or doubling the frequency of the train service. More importantly these days, it is desirable to know the sensitivity of response to possible changes in the policy variable - in the above two examples, public transport fares and frequency respectively. One measure of sensitivity is the commonly encountered term, elasticity, which may be readily obtained from MNL models. As the MNL model can readily be segmented or stratified into different population sub-groups, it can easily be used to determine which sub-groups are the most sensitive to particular policy variables.

The authors contend that MNL models are extremely appropriate in the field of transport policy analysis. This is not to deny that they could be applicable in long term strategic planning. It is in the former area that their superiority over aggregate models is most marked when existing HIS data is all that are available for estimation. Of course, one other often neglected use of MNL models, or for that matter any behavioural-type of model, is that intelligently used, they should increase our level of understanding of the phenomenon that we are attempting to model.

A Consumer Behaviour Theory of Travel

The Lancastrian-characteristics paradigm of consumer behaviour is stated in its simplest form, as:

$$U^k = \sum_{\ell} \beta_{\ell} \, X^k_{\ell} \qquad (2)$$

where U^k is the utility associated with a particular alternative, k;
X^k_{ℓ} is the 'quantity' of each characteristic ℓ, associated with the particular alternative, k;
and β_{ℓ} is the 'weighting' on each characteristic (Lancaster 1966).

This paradigm is well accepted (Hensher 1978a) and is particularly appealling in the field of travel behaviour as it is easier to isolate and define 'characteristics' pertinent to travel and travel decisions than to consider travel itself as a 'good' in its own right. The previous consumer behaviour paradigm was simply that the utility associated with a particular consumption bundle was a function of the quantity consumed of each good in the bundle (Henderson and Quandt 1971). In the case of travel this would mean the more travel the better if we defined travel as the good.

Equation (2) applies at the level of the individual. So there is no reason why the β's cannot vary from individual to individaul; since the same level of characteristic X_i will not necessarily produce the same amount of satisfaction or utility to each individual. Furthermore, the 'mapping' from measureable characteristics (e.g. travel time, travel cost) into the set of characteristics that individuals associate with travel is likely to vary according to the individual under scrutiny. This 'mapping' aspect is not really addressed in the current practice of MNL modelling, except indirectly by considering different functional forms. Again the technique of functional analysis attempts to explore this area more fully (Louviere 1979).

There are some practical problems to overcome in estimating eqn (2). First, our tools for quantifying all the characteristics associated with travel are far from comprehensive. With home interview surveys only information about travel time and travel cost was usually sought (at the level of the individual trip). Such characteristics as comfort, convenience, etc., are yet to be satisfactorily quantified and are therefore replaced by a constant which represents some sort of average value for this subset. Second, because we only have a single observation on any one individual for a particular travel decision, it is necessary to group individuals in order to estimate the set of parameters β_ℓ. Thus, the more homogeneous the group is, with respect to the 'weightings' they attach to each characteristic, the more precise will be the parameter estimates.

Past practice has largely been to estimate just one set of parameters for the whole population, using the whole sample. This has led to estimated equations of low significance, poor goodness-of-fit and which have been unable to reproduce the original sample results satisfactorily (Talvitie 1979à). To overcome the lack of homogeneity in the sample, the practice of including dummy variables of a socio-demographic flavour in the utility function has eventuated. The three deficiences cited above have certainly been overcome by this practice but quite clearly it is at odds with theory of consumer choice behaviour enunciated above.

Apart from being theoretically inconsistent the practice also adds little from the point of view of policy analysis. The sensitivities to changes in level-of-service variables (the only variables over which the decision maker has any control) is dulled by the fact that they represent the weighted averages over the whole sample. Obviously some individuals (or groups of individuals), in the sample will be more sensitive to changes in particular level-of-service (LOS) variables than will others. If these different sensitivities by different groups could be separated out, then a much more powerful tool eventuates. Of course these sensitivities can be separated out simply by estimating separate equations for each (relatively) homogeneous group.

The linear combination of LOS variables for a particular mode is often referred to as the generalised cost of travel for that mode. What amounts to a scaling factor is used to match the units of cost to the level of utility which is dimensionless. Williams (1977) embraces this approach to produce the following equation:

$$U^{nk} = -\lambda^n \left(c_{ij}{}^k + \delta^{nk}\right) \tag{3}$$

where U^{nk} = the utility associated with the k^{th} alternative, for the n^{th} population sub-group;

$c_{ij}{}^k$ = the generalised cost (in money terms) of travel by the alternative mode, k, between i and j;

δ^{nk} = the constant that represents the average effect, again in money terms, of the unquantifiable aspects (e.g. comfort, convenience, etc.,) of travel by the k^{th} alternative, for the n^{th} population sub-group;

and λ^n = a scaling or dispersion parameter, with the units of the inverse of money, for the n^{th} population sub-group.

Note that eqn (3) could also apply at the level of the individual, as do eqns (1) and (2), but for the purposes of estimation, grouped data must be used. Williams (1977) has however recognised the requirement of segmenting into homogeneous sub-groups by the introduction of a subscript, n, to denote person type, and in a later publication he specifically estimated separate models for distinct sub-groups (Williams and Senior 1977 and Senior and Williams 1977).

Equation (3) is related to eqn (2) thus (dropping the subscript for convenience):

$$U^k = \sum_{\ell} \beta_{\ell} X_{\ell}{}^k = -\lambda c_{ij}{}^k - \lambda \delta^k \qquad (4)$$

in eqn (4) $\lambda\delta^k$ represents that subset of $\sum_{\ell} \beta_{\ell} X_{\ell}$ which cannot as yet be quantified (e.g. comfort, convenience, etc.) and $\lambda c_{ij}{}^k$ is that subset of $\sum_{\ell k} \beta_{\ell} X_{\ell}$ that can be quantified. Note therefore that $c_{ij}{}^k$ is also a linear additive function of the (quantifiable) attributes of travel, as λ is only a scalar.

The multi-nomial logit model simply uses the utility associated with each alternative, U_k, in the following manner to produce an estimate of the probability of selecting an alternative, k from a set of alternatives, K:-

$$P_{(k/K)} = \frac{\exp U_k}{\sum_k \exp U_k} \qquad (5)$$

where $P_{(k/K)}$ = probability of selecting alternative k from the set of alternatives, K;
and U_k = is as defined previously.

The formulation of the utility function adopted in eqn (3) allows distinct behavioural differences between sub-groups to be observed. First, different sub-groups may have different δ's which reflects their differing appreciation of the intangible characteristics of travel. Second, different sub-groups may have different λ's, reflecting their differing sensitivities to absolute changes in their (perceived) generalised cost. Third, groups may exhibit different c_{ij}'s (although not specifically allowed for in eqn (3) above), reflecting differing relative weightings on each of the quantifiable attributes of travel. The second and third points of behavioural difference are tied together; nevertheless it may be at times fruitfull to consider them as separate. Only the first point of behavioural difference is able to be established if a single utility function is estimated for the whole population using socio-economic dummy variables. The effects of the first point of behavioural difference and the second point of behavioural difference, known as the 'shift' effect and the 'slope' effect respectively, on the probability function generated by the MNL model are illustrated in Fig 1.

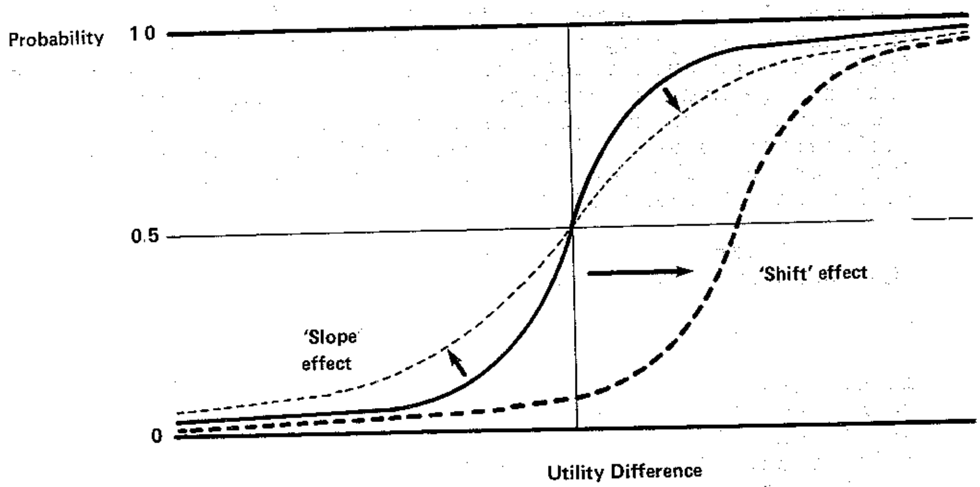

Fig 1 – 'Shift' and 'Slope' effects in a binary choice

The Assumption of Trip Independence

A hangover from the days of aggregate modelling is the implicit assumption that each trip made by an individual is quite independent of, not only trips made by any other individual, but also any other trips made by that individual. This assumption may be inconsequential if travel consists overwhelmingly of simple purpose outings with the home residence as the focus. Recently some attention has been drawn to the importance that the linking of activities (purposes) plays in travel behaviour (Hensher 1976, Morris, Dumble and Wigan 1979), and Adler and Ben-Akiva (1979) and Lerman (1979) formulate and estimate models which allow for changes in activity linking to occur. However, apart from these and a few other examples, modellers have continued with this trip independence assumption. Figure 2 illustrates the problem.

Figure 2a and Fig 2b depict two different travel patterns that accomplish the same activity pattern. The decisions faced by someone that might end up under-taking an activity pattern such as (a) or (b) would be: 'Which activities do I wish to pursue?'; 'At what times and where do I wish to pursue them?'; and 'By what means (i.e. mode) will I get to the activity sites?'. Naturally there is a large degree of interaction between these decisions, but if one decision was to be modelled by itself, as is often the case, then the influence of the other decisions must first be eliminated. For example, if modal choice is the criterion decision, then it should be examined on

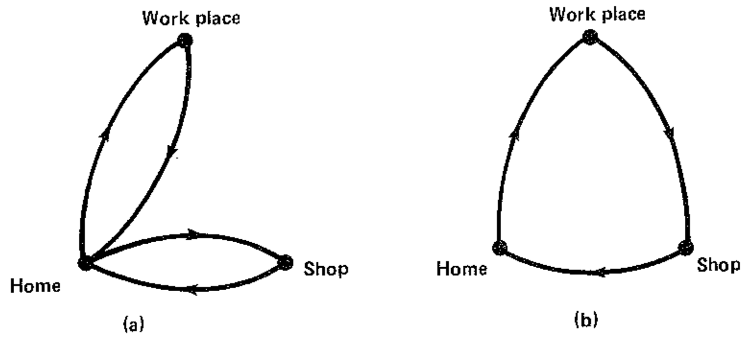

Fig 2 — (a) Two 2-stage journeys
(b) One 3-stage journey

the condition that its destination, timing and linking are known. An even more specific example would be that if one were to model modal choice for the journey-to-work, the linking condition (as well as the destination and timing conditions) should be accounted for. Referring again to Figs 2a and 2b, the linking conditions of 2a may result in a different mode choice equation from that which results from the conditions represented in 2b.

Estimation and the Range of Observations

One aspect of current modelling practice often overlooked is that of the range of observations for each independent variable. This has consequences for prediction and interpretation.

Any model is after all only an approximation. If it is used for prediction when all the independent variables take values within the range over which the estimating set spanned, then the modeller can be reasonably confident that his approximate answer will not be too far off the mark. In fact, he can, calculate statistical confidence limits on his answer. On the other hand if some independent variables take values outside their observed range then the resultant answer is unknown in terms of its precision. A particularly good example of this would be predictions about the effects of doubling or quadrupling the price of petrol. When the new value for the independent variable 'car out-of-pocket cost' is calculated, a significant number of the population will have a value for 'car out-of-pocket cost' well outside the range of this variable found in the estimating set. Outside this range a completely different pattern of behaviour may prevail. In other words the functional relationship between utility and 'car out-of-pocket cost' approximated by the estimated model may be completely inappropriate once outside the estimation range.

Interpretation cannot be meaningful unless the range of observations is borne in mind, particularly when generic variables are used. For example, 'access time' is a variable common to most modes. Thus when modal choice is being modelled 'access time' is usually specified as a generic variable. However the range of access times observed for each mode is likely to vary considerably. In almost all areas of a city, excepting the central areas, 'access time' for car drivers and car passengers is likely to be quite small. On the other hand, in precisely these same areas the access time by public transport is likely to be quite large. Thus if only observations from suburban areas are used, there will be two distinct clusters of 'access time' and the co-efficient estimated for 'access time' may well be a reflection of the slope of a straight line drawn between the centres of these two groups. In extreme cases this slope could result in a negative sign on the co-efficient. In such extreme cases, of course, 'access time' should be treated as a alternative - specific variable.

A CASE STUDY : MODAL CHOICE IN BALLARAT

Ballarat Home Interview Survey Travel Data

In an attempt to demonstrate or investigate the importance of these issues raised above, HIS data from the Victorian provincial city of Ballarat (population 55,000 in 1970, the year of the HIS) were analysed and several MNL models of journey-to-work were estimated and are reported below.

Ballarat HIS was conducted as part of the Ballarat Transportation Study (Harris Lange - Voorhees 1971). Details of the HIS procedures are also contained in Dumble (1979). Generally speaking this HIS was certainly no worse than most others in many respects and superior in one or two important areas: in particular, the collection of information about *all* personal trips, including on-foot and on-bicycle which was unusual for the time (see Dumble 1979). This, coupled with the facts that the data were stored in an easily manageable format and that the full data set was of a convenient size, meant that the Ballarat HIS data set was a suitable one on which to begin investigations.

Journey-to-Work in Ballarat

Journey-to-work modal choice has been the subject of much investigation, for which there are several reasons. First, the journey-to-work usually accounts for the largest proportion of trips by any single purpose. In Ballarat this was no exception; it accounted for some 22 per cent of all trips. Second, the journey-to-work trip is the easiest to understand in that it is repetitious and is usually invariant for any particular individual in both time-of-day and destination.

If the conventional classification of trips used in transportation modelling is followed, i.e. each trip is treated as an independent event and dominant mode coding is used to ensure that only one mode is recorded for any one home-to-work, or vice versa, trip (i.e. 'linked' trips are used not 'unlinked' trips), then the breakdown of journey-to-work trips by mode is as listed under model 1 in Table II.

THE ESTIMATION PACKAGE; MLOGIT

The MLOGIT program was used to estimate all the models reported below. Details of this program are available elsewhere (Hensher 1978b, Goschnick 1980), but some of its limitations should be mentioned here. First, there is an upper limit of 20 explanatory variables allowed for any single model estimation. Initially this sounds quite reasonable, however there is a further limitation caused by the peculiarities of the data input requirements of the MLOGIT program. Variables enter MLOGIT in the form of differences. For example, 'in-vehicle travel time' (IVT) is entered as the difference between 'in-vehicle travel time' for the chosen mode and each of the rejected alternatives. Hence, a modal choice model having, say four alternatives, will require the input of three variables difference values for each explanatory variable i.e.

(IVT chosen - IVT alternative 1)
(IVT chosen - IVT alternative 2)
(IVT chosen - IVT alternative 3)

This particular treatment of data for each alternative is not unique to MLOGIT. On the contrary, it is the key to the mathematical benefit derived from adherence to the IIA assumption, by which all multinomial logit programs gain. However, the requirement of having the data in this format *before* entering the program, is peculiar to MLOGIT. So, while the input format itself is not restrictive, it does necessitate a large degree of data pre-processing.

While the second limitation is not overly restrictive for a binary or three alternative choice situation (i.e. 20 explanatory variables require input of 20 and 40 variable difference values, respectively), the modelling of say six alternatives (as is the case in the exercise reported below) results in a severe limit of only eight explanatory variables. This meant that one question which the authors had hoped to investigate could not be fully addressed. Namely, should certain level-of-service (LOS) variables such as 'in-vehicle travel time', 'access time' etc., be included in models as mode-specific variables or, as generic variables as is usually the case (e.g. Hensher 1979a).

Simulation of LOS Variables

The HIS data contains very few LOS variables; 'total travel time' by the chosen mode for all trips was recorded as the difference between 'start' time and 'end' time, as was 'fare' for trips made by public transport. However, even for these, the corresponding values for modes *not* chosen, were obviously not recorded. So it was necessary to simulate all LOS variables, for all recorded trips, for the full mode choice set. To this purpose a computer model of Ballarat was built up, using the ARRB in-house traditional transport package, TRAMP. A brief description of the simulation follows. The full account can be read elsewhere (Goschnick 1980).

Road, public transport, walk and other (bicycle and motorcycle) networks were superimposed on to one another to represent the complete Ballarat transport system. The public transport network included both bus and tram (which was still in operation in 1970) routes. The networks were based on a 130 traffic zone breakdown of Ballarat, as used for the Ballarat Transportation Study (Harris Lange-Voorhees 1971).

The relevant network parameters were set as follows:

(a) Road network link speed; 48 km/h.
(b) Road network zone connector speed; 32 km/h.
(c) Private vehicle out-of-pocket running cost; 2.8¢/km (the cost of running a six cylinder sedan in 1970).
(d) Taxi fare; 12.4¢/km plus a 20¢ flagfall.
(e) Tram route speed; 35 km/h.
(f) Bus route speed; 40 km/h.
(g) Public transport fare stage; 5.5¢ (a variable fare-stage function is not available in the TRAMP package).
(h) Public transport wait time; set to a third of the headway.
(i) Bicycle speed; 20 km/h.
(j) Walk speed; 4.8 km/h.

The access mode to public transport was assumed to be 'walk', except where the trip origin zone was considered to be far removed from the public transport system, in which case 'car passenger' was the assumed access mode.

The optimum path seeking algorithm of the TRAMP program produced directly the LOS variables: car, car passenger and taxi in-vehicle times; car out-of-pocket running costs; taxi fare; public transport in-vehicle time, fare, access time and wait time; walk time; and cycling time, for all zone pairs. Access time for car and car passenger was assumed to be three minutes if the trip began or ended in a CBD zone, and one minute if the trip began or ended in an outer zone. Wait time for a taxi was assumed to be five minutes.

The ranges of LOS variables over which each of the models was estimated are represented in Table 1.

Description of Journey-to-Work Models Estimated

As was indicated in the first part of this paper the initial journey-to-work model estimated, corresponded to that commonly adopted; viz-all trips with one end as 'home' and the other as 'work', irrespective of:

(a) what other trips were made on the same journey; and
(b) the socio-economic characteristics of the traveller.

Further, the model was a simultaneous one and therefore, each mode was implicitly assumed to be equally dissimilar to every other mode; there was no hierarchy of modes. The important departure from common practice was that only LOS attributes were used as explanatory variables.

The parameter estimates of model 1, and for all subsequently estimated models appear in Table 2. Discussion of these parameter estimates is left until the next section. The significant feature of model 1 is that a full sample enumeration results in some 62.4 per cent of cases being correctly 'forecast' by it. However, this relatively good result is superficial as model 1 actually predicted that in every case the mode taken would be 'car driver'. As Table II indicates 62.4 per cent of travellers in the sample did travel as car drivers.

Model 2 had the same specification as model 1 but those home-work trips that were part of a longer journey sequence were eliminated from the estimation set. Thus only those trips that were part of a simple two stage journey (as depicted in Fig 2a) were included. Once again the superficially good result for the full sample enumeration was due to the fact that every case was 'forecast' to travel as a 'car driver'.

The fact that the sample was so heavily dominated by the car driver mode is a problem in itself. MNL models perform best when there are about even number choosing each alternative. The subsequent models were much better in this regard, which may be another advantage in this whole approach.

TABLE 1

LOS VARIABLE RANGES FOR EACH MODEL

Model	Low 1	High	Low 2	High	Low 3	High	Low 4	High	Low 5	High	Low 6	High
1. Car Driver												
-IVT	0.2	19.3	0.2	16.5							0.2	15.5
-Cost	0.3	41.6	0.3	35.9							0.3	33.0
-AT	2.0	6.0	2.0	6.0								
2. Car Passenger												
-IVT	0.2	19.3	0.2	16.5								
-Cost											0.2	16.5
-AT	2.0	6.0	2.0	6.0								
3. Public Transport												
-IVT	0.1	23.0	0.1	23.0	0.1	17.7	0.1	15.4	0.1	17.7		
-Cost	5.5	55.1	5.5	55.0	5.5	54.4	5.5	48.9	5.5	54.4		
-AT	0.8	52.9	0.8	48.4	1.4	48.4	1.7	23.4	1.4	48.4		
4. Taxi												
-IVT					0.3	13.3	0.3	11.5	0.3	13.3		
-Cost	21.3	205.6	21.3	178.6	22.3	143.8	22.3	121.8	22.3	143.8		
-AT	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0		
5. Walk												
-Walk Time	1.3	188.4	1.3	160.1	2.0	125.6	2.3	103.1	2.0	125.6		
6. Bicycle												
-Cycle Time	0.3	44.4	0.3	38.0	0.5	29.7	0.6	24.4	0.5	29.7		

Note: Where AT = Access time for modes 1, 2 and 3
= Wait time for mode 4
IVT = In-vehicle time
Cost = Car running costs for mode 1 and fares for modes 3 and 4.
All times are in minutes and all costs in cents. See Table II for model specifications.

TABLE 2

ALTERNATIVE MODELS OF MODE CHOICE FOR JOURNEY-TO-WORK IN BALLARAT.

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6
DESCRIPTION OF MODEL						
Market Segment[1] :	All	All	All–NC	U–NC	L–NC	LG–C
Journey Type[2] :	All	2S	2S	2S	2S	2S
Number of obs. :	3 488	3 120	697	446	251	474
VARIABLES IN MODEL[3]						
Car driver	2176[4]	1939				251
– access time	**–0.19107** *(–10.43)*	**–0.19008** *(–9.83)*				
– in-vehicle time	**0.02283** *(0.43)*	**0.01179** *(0.21)*				**0.23768** *(0.126)*
– cost	**–0.05463** *(–9.95)*	**–0.05700** *(–9.64)*				**–2.4859** *(–6.94)*
– constant	**1.2833** *(17.89)*	**1.29560** *(17.12)*				
Car passenger	540	484				223
– access time	**–0.19107** *(–10.43)*	**–0.19008** *(–9.82)*				
– in-vehicle time	**–0.11221** *(–1.92)*	**–0.12506** *(–2.00)*				**0.23768** *(0.126)*
– cost	–	–				**–2.4859** *(–6.94)*
– constant	–	–				**–1.8911** *(0.535)*
Public transport	172	153	153	34	119	
– access time	**–0.19107** *(–10.43)*	**–0.19008** *(–9.83)*	**–0.11062** *(–3.12)*	**–0.10759** *(–2.60)*	**–0.1129** *(–1.54)*	
– wait time	–	–	–	–	–	
– in-vehicle time	**0.03604** *(0.97)*	**0.03329** *(0.84)*	**–0.22812** *(–2.93)*	**–0.22451** *(–2.64)*	**–0.33863** *(–1.70)*	
– fare	**–0.05463** *(–9.95)*	**–0.05700** *(–9.64)*	**0.00600** *(0.34)*	**0.00971** *(0.43)*	**–0.00016** *(–0.004)*	
– constant	–	–	–	–	–	
Taxi	21	16	16	2	14	
– wait time	**–0.19107** *(–10.43)*	**–0.19008** *(–9.83)*	**–0.11062** *(–3.12)*	**–0.10759** *(–2.60)*	**–0.1129** *(–1.54)*	
– in-vehicle time	–	–	**–0.60563** *(–2.70)*	**–0.62127** *(–2.44)*	**–0.72972** *(–1.43)*	
– fare	**–0.05463** *(–9.95)*	**–0.05700** *(–9.64)*	**0.00600** *(0.34)*	**0.00971** *(0.43)*	**–0.00016** *(–0.004)*	
– constant	–	–	**–1.1730** *(–2.05)*	**–1.1198** *(–1.78)*	**–1.5270** *(–1.03)*	
Walk	357	327	327	146	181	
– total time	**–0.05139** *(–7.46)*	**–0.05250** *(–7.11)*	**–0.12884** *(–9.44)*	**–0.12618** *(–8.14)*	**–0.14455** *(–4.48)*	
– constant	–	–	**3.0204** *(9.85)*	**2.7220** *(7.22)*	**3.6719** *(6.44)*	
Other (Bicycle & Motorcycle)	222	201	201	69	132	
– total time	**–0.18571** *(–6.55)*	**–0.18979** *(–6.25)*	**–0.23870** *(–4.65)*	**–0.22414** *(–4.01)*	**–0.32804** *(–2.51)*	
– constant	–		**0.79325** *(2.65)*	**0.58932** *(1.64)*	**1.3925** *(2.45)*	
MODEL PERFORMANCE						
– *degrees of freedom*	7	7	6	6	6	2
– *2 Log λ*	316.94	263.64	300.51	189.43	99.14	552.00
– ρ^2	0.0388	0.0360	0.1902	0.1788	0.2016	0.8422
– *% correct*	62.4[5]	62.2[5]	58.1	60.3	62.6	99.0

Notes:
1. 'Market Segment Code : NC – Non-Car Modes; C – Car Modes; U – Unlicenced; L – Licenced; G – in a Group of two or more travellers
2. Journey Type Code : 2S – Two Stage travel only; All – Two Stage and Multi-Stage Travel
3. Bold-Type figures are the variable co-efficients and figures in italics and parentheses are t-test values
4. Numbers in this type-face indicate the number of observations
5. This result is misleading as all travellers were 'predicted' to travel as car drivers by this model

The stringent requirements of the IIA assumption could perhaps be better accommodated by a hierarchical or nested approach to mode-choice modelling when several alternatives are available. It may be reasonable to assume that people do not necessarily make an instantaneous choice between all possible alternatives, but that they perceive that distinct groups of alternatives are available. They initially choose between the grouped alternatives and then choose an alternative from within the chosen group (Williams 1977, McFadden 1979, Hensher 1979b). There is some evidence, or at least speculation, that, in small cities such as Ballarat, the initial mode choice is between car and non-car, and the subsequent choice in the non-car group between bus and walk (Morris *et al.* 1979).

It was therefore decided to group 'car driver' and 'car passenger' together as one initial alternative and the remaining four as the other. The characteristics that distinguish between these two grouped alternatives naturally embody the characteristics of the individual modes, or elemental alternatives, themselves. To embody these characteristics algebraically into a model requires the estimation of the second level of choice, i.e. the 'within group' choice, first. The 'inclusive price' or 'logsum' term that emerges is then passed up to the 'between group' choice level (Williams 1977, McFadden 1979). That is, it is necessary to estimate the lower order choice model first.

Model 3 was estimated on all non-car two stage journeys-to-work for which there were some 697 observations which, except for 'taxi' were relatively evenly spread across the modal alternatives. As Table 2 shows, model 3 'predicts' the chosen mode correctly in 58.1 per cent of cases. Although this percentage is lower than the 62 per cent for models 1 and 2 it should be pointed out that for the 697 observations of model 3 not one was correctly predicted by models 1 and 2 - recall that all cases were predicted by models 1 and 2 to travel as 'car driver'. Thus for this sub-sample, model 3 is a much better model at least in terms of reproducing the observed behaviour.

The next aspect to be investigated was that of market segmentation. Since already the distinction was made between 'car' and 'non-car' a logical means of market segmentation would be by some attribute pertaining to car ownership or usage. Williams and Senior (1977), amongst others, have used level of car ownership as the market segmentation attribute, however analysis of the Ballarat data (to be reported by the authors at a later date) indicated that the single most important attribute in 'explaining' differences in travel behaviour was that of possession or not of a current driver's licence.

Thus models 4 and 5 were specified exactly the same as was model 3, but the data used to estimate them were segmented into'unlicenced' and 'licenced' travellers respectively. The results of the full sample enumeration of models 4 and 5 show an improvement over that of model 3. Model 4 correctly 'predicted' in 60.3 per cent of cases and model 5 in 62.6 per cent. In actual numbers, models 4 and 5 combined,correctly 'predicted' 426 cases out of the 697, compared to model 3 which correctly predicted in 405 cases. Neither approach predicted any traveller to use taxi, which was probably due, in part, to the small number of observations involving taxi travel. It would probably have been best to have removed taxi trips from the data set altogether, and eliminated 'taxi' as an alternative.

The final model reported upon here is model 6, which represents the lower level of the 'car' group of alternatives. Model 6 evolved after some experimentation within this 'car' group, it is not the 'car' group equivalent of model 3 in the 'non-car group. Such a model proved impossible to estimate, even when the data were segmented into 'licenced' and 'unlicenced' travellers. Of course, once the 'licence'/unlicenced' segmentation is adopted, those 'unlicenced' travellers who are in the 'car' group naturally must fall into the 'car passenger' (elemental) alternative, hence *no* model is required.

To overcome the problem with 'licenced' travellers, another means of partitioning the data was tried. It is reasonably common practice for the purposes of modal choice modelling to define 'car driver alone' and 'car driver with passengers' as separate modes (e.g. Pak Poy and Associates 1978). It was decided to extend this concept a little further by distinguishing between persons travelling by themselves and those travelling in a group, irrespective of the mode chosen. It does not seem unreasonable to expect that this factor may influence the choice of mode, particularly if 'car driver' and 'car passenger' are identified as distinctly different modes. Unfortunately, the data do not allow the identification of whether the traveller was alone or accompanied, for any mode other than car. When 'car driver' was the chosen mode the number of passengers in the car was recorded and naturally, if going as a 'car passenger', the traveller must have been accompanied by at least one other person.

Model 6 was estimated on the sub-sample data set consisting of all travellers licenced to drive a car and who actually travelled in a group in a car. It was binary choice between 'car driver' and 'car passenger'.

Unfortunately there were very little differences between LOS variables for 'car driver' and those for 'car passenger'. The only variable that had some scope for variation was that of'cost', or more precisely cost sharing between the driver and his/her passengers. The following approach to cost sharing was adopted. If the chosen (i.e. observed) mode was 'car driver' then it was assumed for the sake of calculating the cost of 'car driver', that all persons in the car shared equally the total car running costs. The cost of the alternative mode, 'car passenger' was assumed to be one half the total car running costs. If on the other hand the chosen mode was 'car passenger', then the perceived cost of 'car passenger' mode was also assumed to be one half of the total car running costs. (The number of people in the car was not recorded when the mode was 'car passenger'). The cost of the 'car driver' mode, the alternative mode in this case, was assumed to be the full car running costs.

The full sample enumeration that resulted from model 6 is extremely encouraging; only five observations out of 474 (or one per cent) were incorrectly predicted.

What emerged from the successive modifications to the original, and commonly adopted, mode choice specification was a relatively complex model of individual choice behaviour. The emergent model is illustrated in Fig 3 which is split into two segments, one for travellers who do not possess a driver's licence and one for those who do. Models 4, 5 and 6 do not exhaustively cover the models required to fully specify the overall model depicted in Fig 3. The additional models are all of a higher order and therefore require the 'passing-up' of a logsum or inclusive price. This is the next phase in the modelling exercise.

Models 4, 5 and 6 do not fully cover all the elemental alternatives. Neither 'car driver alone' nor 'unlicenced' car passengers are covered. In fact, of the 3120 two-stage journeys-to-work, only 1171 (or 37.5 per cent) are covered by models 4, 5 and 6. A measure of the improvement that the above modelling approach offers over the more commonly adopted approach is that for these 1171 observations, model 1 correctly predicted the chosen mode in 251 (21.4 per cent) of cases (i.e. in the 251 cases where 'car driver' was actually chosen), whereas the structured and segmented approach resulted in correct predictions in 895 (76.4 per cent) of cases.

Interpretation of Model Estimates

The form of the utility function specified by eqn (3) earlier makes comparisons between the models a little easier to comprehend. The conversion from the simple form of Table 2 to that in eqn (3) is achieved by setting λ equal to the co-efficient for the actual money cost variable (which was always specified as generic). Table 3 presents the results of this transformation for model 1.

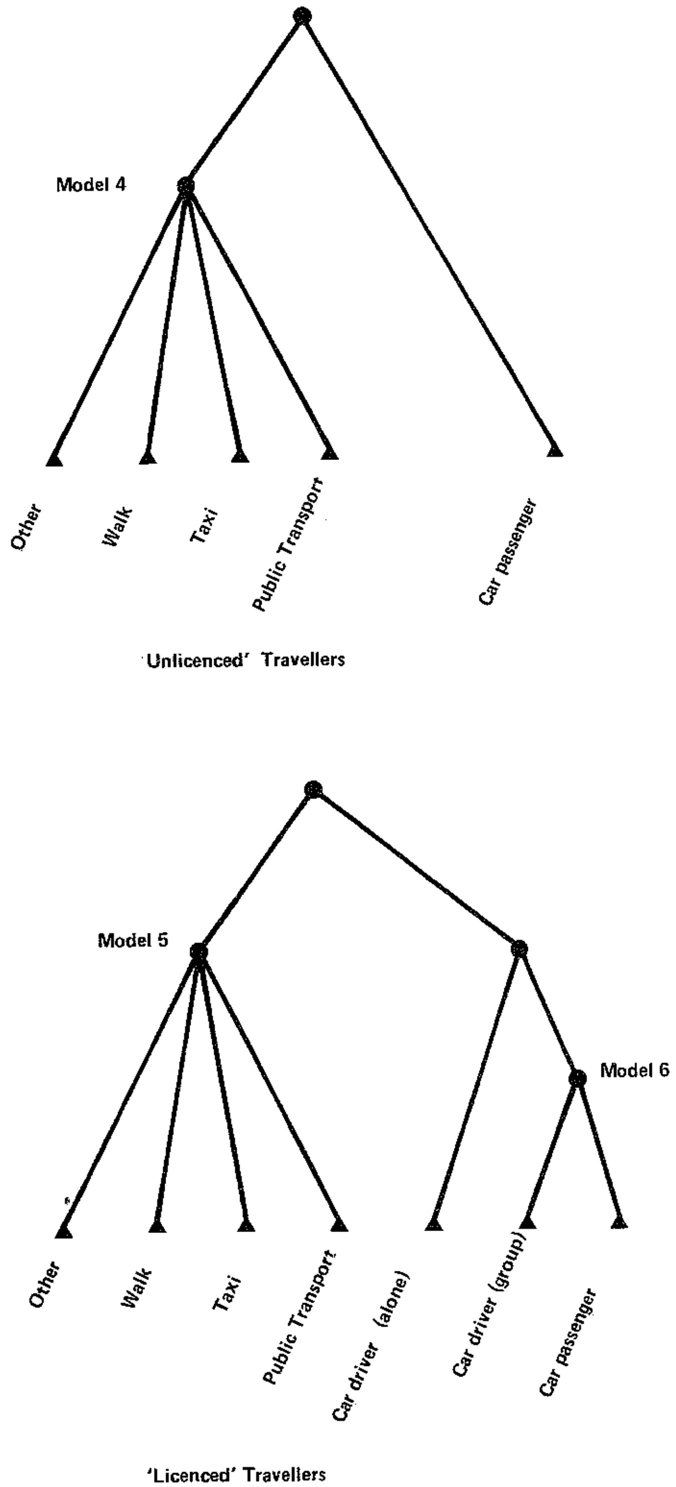

Fig 3 — Hierarchical mode choice model of journey — to-work in Ballarat

TABLE 3

MODEL 1 EXPRESSED IN GENERALISED COST FORM

$\lambda = -0.05463$

		c_{ij}^k	δ^k
1.	Car Driver	3.498AT - 0.418IVT* + COST	-23.49
2.	Car Passenger	3.498AT + 2.054IVT	0
3.	Public Transport	3.498AT - 0.660IVT* + COST	0
4.	Taxi	3.498AT + COST	0
5.	Walk	0.941 TIME	0
6.	Other	3.399 TIME	0

Note:

Where AT = Access time for modes 1, 2 and 3
= Wait time for mode 4
IVT = In-vehicle time
COST = Car running cost for mode 1, and fares for modes 3 and 4
TIME = Total journey time.

* Not significant at the five per cent level.

One problem that can be encountered when expressing model results in this manner is that the 'cost' variable may not be significantly different from zero, or, even worse, it may be significantly different from zero and have the wrong sign. In the cases of models 3, 4 and 5 the 'cost' variable was not significantly different from zero. For the sake of interest however the remaining model results (i.e. models 2 and 6) are expressed in the generalised cost form in Table 4 and 5 respectively.

It is dangerous to draw too many implications from the results of Table 3, 4 and 5 and indeed from Table 2. However there is the advantage that each of the subsequent models are estimated on sub-sets of previously estimated models, and therefore statistical tests of significance are easily made. For instance, to test whether or not the co-efficient estimate for a particular variable varies between models, the test statistic is simply:

$$t = \frac{\hat{\beta}' - \hat{\beta}}{S'}$$

where $\hat{\beta}'$ = is the estimate obatined from the full set, (i.e. a preceeding model)
$\hat{\beta}$ = is the estimate from the model in question
and S' = is the standard deviation (estimate) associated with the estimate obtained from the full set.

Space requirements prevent the reporting of all possible significant test results here, but some of the more interesting ones are now discussed. Returning to the generalised cost specification of Tables 3, 4 and 5 it appears that the estimate of λ for model 6 is easily significantly different at the one per cent level from either estimates of λ for models 1 and 2. However, there is no significant difference between the estimate of λ for model 2 and that for model 1 at the five per cent level.

TABLE 4

MODEL 2 EXPRESSED IN GENERALISED COST FORM

$\lambda = -0.05$			
		c_{ij}^{k}	δ^{k}
1.	Car Driver	*3.335*AT − *0.210*IVT* + COST	−22.73
2.	Car Passenger	*3.335*AT + *2.194*IVT	0
3.	Public Transport	*3.335*AT − *0.584*IVT* + COST	0
4.	Taxi	*3.333*AT + COST	0
5.	Walk	*0.921* TIME	0
6.	Other	*3.330* TIME	0

Note:

Where AT = Access time for modes 1, 2 and 3
= wait time for mode 4

IVT = In-vehicle time
COST = Car running costs for mode 1, and fares for modes 3 and 4
TIME = Total journey time.

* Not significant at the five per cent level.

The direction of change in λ is reasonable. The hypothesis in the first part of this paper was that as a greater degree of homogeneity was achieved by each step of market segmentation or data partitioning, then the greater the sensitivity, as measured by λ, that that sub-group would exhibit with respect to changes in generalised costs.

There are several general features of Table II that should be commented upon. The first, is that in every instance LOS variables that were significant had the correct sign. The second, is that there was a consistency in the patterns of those variables that were not significant. For instance, 'in-vehicle time' was never significant for the 'car driver' mode ('in-vehicle time' was specified as alternative-specific rather than generic, except in model 6). Yet it was significant for the 'car passenger' mode. Similarly public transport 'in-vehicle time' was not significant in the fully simultaneous models 1 and 2, but became much more significant in models 3, 4 and 5; the models pertaining to the non-car group of alternatives. As well, for models 3, 4 and 5 'fare' was not significant yet it had been in models 1 and 2.

TABLE 5

MODEL 6 EXPRESSED IN GENERALISED COST FORM

$\lambda^1 = -2.4859$

		$c_{ij}{}^k$	$\delta^{1\ k}$
1.	Car Driver with Passengers	-0.096IVT* + COST	0
2.	Car Passengers	-0.096IVT* + COST	0.76

Note:

Where AT = Access time for modes 1, 2 and 3
= Wait time for mode 4
IVT = In-vehicle time
COST = Car running costs for mode 1, and fares for modes 3 and 4
TIME = Total journey time.
and the subscript '1' indicates the 'licenced' segment of the sample

* Not significant at the five per cent level.

These results are open to interpretation, but it would seem reasonable to assume that the lack of significance of particular variables is at least in part due to that variable not being influential on the choice outcome, and not entirely due to measurement, mis-specification and other errors which are surely present. Thus, for this set of travellers, it can be tentatively concluded that for their journey-to-work the 'in-vehicle time' for the 'car driver' mode is not really a factor that influences their choice of modes. Furthermore, for that sub-set of travellers who travelled to work by one of the four non-car group of modes (697 of them), the cost or fare paid for the trip does not appear to be a significant factor in their choice of mode. For that group of travellers who travelled to work in a group in a car the cost sharing arrangements may be the most important factor in determining who drives.

It is important to realise the conditional nature of these results. That is for instance, the choice of whether or not to travel in a group may be very sensitive to travel time, but, having decided to travel in a group in a car, travel time ceases to be an important factor in subsequent decisions. Thus the importance of each LOS variable cannot be fully appreciated until the complete model is estimated (see Fig 3).

LIMITATIONS OF THE APPROACH

In the first part of this paper several advantages of the outlined modelling approach were put forward. In gaining those advantages it is inevitable that it would be at the cost of incurring some disadvantages.

More Segmentation VS More Data

The most obvious disadvantage is that the proposed modelling structure (see Fig 3) requires the estimation of more equations or sub-models than does the current approach. It is not so much the extra expense involved in either estimating these sub-models or running them in a production mode, but the extra data requirements, that is the disadvantage. In our example there was no problem as there were plenty of observations to begin with, but inevitably when one model (e.g. model 1) is replaced (eventually) by 4 sub-models for the 'licenced' segment of the population and a further 2 sub-models for the 'unlicenced' segment, obtaining sufficient data could be a problem. For instance adopting the same methodological approach for 'personal business' journeys instead of 'work' journey still using the 1970 Ballarat HIS data, would have meant only starting with 434 observations for model 1 and the rejection of 178 (41 per cent) of those when proceeding to model 2 (2 stage journeys only). (This is not to suggest that 'personal business' travel should be modelled with exactly the same hierarchical structure and the same market segmentation schema, as one point being made is that a much more flexible approach to modelling travel behaviour, still within the confines of MNL and HIS data, should be adopted. This flexibility should encompass the predictive tasks that await the final model and the insights that pre-modelling analysis of input data provide).

'A problem with adequate sample size' is often the argument advanced against market segmentation and by inference, in favour of the inclusion of socio-economic variables directly into the utility function. It is certainly conceded that there must be balance struck between the extent of market segmentation and the number of observations available to estimate any model, but it does seem most logical to at least investigate the appropriateness of the restrictive assumption implicitly brought about by the inclusion of socio-economic variables directly into the utility function (i.e. that they only have a 'shift' effect and not a 'slope' effect - see Fig 1) when there are sufficient data to do so.

How to Deal with Multi-Stage Travel

A more complex problem is that caused by the removal of multi-stage journeys from the estimation set. The importance of multi-stage journeys (see Fig 2b) is increasingly being recognised (e.g. Hensher 1976 and Morris *et al.* 1979) but so far little progress has been achieved modelling them. There would seem to be at least two fronts on which to proceed: either 2 stage and multi-stage journeys can be modelled separately but not independently (e.g. recursively); or the 'trip' as the unit of analysis can be dispensed with completely and replaced with 'journey' (or 'sojourn') whether 2 stage or multi-stage. Either way, the 'activity' view of travel behaviour would seem likely to emerge in place of the current 'trip-pupose' view.

An interim, practical, solution may be to postulate an hierarchy of trip purposes (or activity types) and use it in rather the same manner as 'dominant mode coding' is used. That is, to make the assumption that say 'work' is the most dominant acitivity, as far as mode choice is concerned, and that any activities coupled with the journey-to-work (e.g. personal business) do not influence the choice of mode. Thus our models 2, 3, 4, 5 and 6 would be re-estimated with the 3 stage journeys (involving a work trip) included in the estimation set. This seems reasonable in view of the fact that none of the co-efficient estimates of model 1, (i.e. with all journeys included) were significantly different to those of model 2 (estimated without multi-stage journeys). If, say, 'personal business' was the next most dominant purpose then the mode choice model for 'personal business' would be estimated on the data set containing all 2 stage 'personal business' journeys plus all those multi-stage journeys that contained 'personal business' trips except those that also contained a 'work' trip. This procedure would continue down to the least dominant trip purpose, which model would be estimated solely on 2 stage journeys.

The only remaining problem is to determine the ordering of trip purposes from most-dominant to least-dominant. This may have to be determined arbitrarily, but some sensitivity testing (of the order) may help.

Functional Form

A further limitation, rather than problem, with the approach so far, is that only the linear form of the LOS variables was investigated. Various transformations of the level-of-service variables (e.g. logarithmic) have been tested by others and it is now possible to systematically investigate functional form with the aid of Box-Cox and Box-Tukey transforms (see Gaudry and Wills 1978, Johnson 1979 and Hensher and Johnson 1979).

It is also possible to investigate different functional forms of LOS variables using socio-economic variables; the most common being the division of money cost variables by income (see for example Charles River Associates 1976).

Although the results of such transformations have been encouraging they were not investigated at this stage in the interests of keeping the exercise as simple as possible. Certainly, it is an area worthy of further investigation and will form part of a later stage in the current project, but consideration of functional form takes us into the very complicated and complex area of 'perceptual' measures versus physical measures.

Perceptual VS Actual Measures

The specification of physical measures instead of perceptual measures would be a mis-specification of the utility function, if the two did not co-incide, and would result in errors in any model estimated on such data (Koppelman 1976). In a sense, experimentation with functional form is attempting to determine how individuals 'map' physical measures (e.g. LOS variables) into perceptual ones.

In the general case where network simulation is used to produce LOS measures there is an additional source of error; measurement error; due to the reported values of these variables not being the actual values (Koppelman 1976). The use of zonal averages (for that is what the network simulation approach results in) has been suggested by Horowitz (1979) as being one of the largest single sources of error in individual choice (MNL) models. However Horowitz's comments appear to be more directed at the use of zonal averages for socio-economic variables than for LOS variables which may go much closer to meeting the stringent conditions required to prevent biased estimates (Horowitz 1979). In the case being discussed here the simulated LOS variables may well meet Horowitz's conditions as the zones themselves are relatively uniform in size and shape and are small in comparison to most zonal systems adopted for travel analysis (see Dumble 1979), therefore minimising both the in-zone and between-zone variance. Hensher (1977) concludes that reported travel times (i.e. starting time/ finishing time) are close to the true and perceived time and, as our simulated times compared well with reported times, it is suggested that in this case the error introduced by simulation on a zonal basis of LOS variables (particularly travel times) should be less than the amount suggested by Horowitz (1979). An obvious conclusion in this regard must be to place strong emphasis on the specification of network characteristics (i.e. link speeds, distances, cost and fare functions, etc).

These drawbacks and limitations are not necessarily unique to the approach outlined above. Nevertheless it was important that they be raised, as their airing immediately opens up areas for further refinement.

FUTURE DIRECTIONS

The investigation as outlined earlier is not yet completed as the higher models have not been estimated. However it is certainly not premature to include in this paper a section dealing with future research directions, still within the confines of HIS data and network simulation of LOS variables.

In view of the discussion in the immediately preceding section on functional form and 'perceptual' vs 'actual' LOS data, an obvious area for further research awaits us there.

A computer package, BLOGIT, is now available which incorporates Box-Tukey transforms and therefore enables the systematic investigation of functional form (Crittle and Johnson 1980). It is the intention of the authors to re-estimate many of the models reported in Table II using this package.

A further intended refinement is to make use of the 'unlinked' travel data to investigate more fully the access mode/primary mode relationship. For our exercise the 'linked' trip was used in which only the most dominant mode appears; information about any access modes having been removed. As described earlier, all LOS variables including access times, etc, were simulated. However, only cursory checks were made of simulated access LOS against actual (i.e. recorded) access LOS.

Recent investigations have suggested that the choice of access mode has some influence on the eventual choice of the dominant mode and Talvitie (1979b) has produced an hierarchical access mode/primary mode individual choice model. In a small relatively uncongested city such as Ballarat, access mode is probably not important, but in larger Australian cities, where it is thought that a need exists to attract travellers out of their cars and back onto public transport, it may be an important factor influencing the likelihood of this modal shift occuring. For this reason it it suggested that access mode be investigated on HIS data from larger Australian cities.

Related to the point of more detail about access mode is the possibility that perhaps more detail is required about aspects of travel time. Access time, wait time and in-vehicle time are already separated out, but it has been suggested that within 'in-vehicle time' further subdivision into 'time stopped' and 'time moving' may significantly improve the explanatory power of models (Hensher and McLeod 1977). Thus any work put into improving network specification, particularly intersection delays, should be repaid in terms of improved models.

Of course, none of these foreshadowed improvements gets to the heart of the 'perceptual' versus 'actual' issue. Unfortunately the use of HIS data and network simulation preclude the use of 'perceptual' data. However the collection of reliable 'perceptual' data is fraught with pitfalls too. For instance asking people how long it would take them to complete a certain trip by an alternative mode does not always elict the correct perceptual or behavioural response. However, whether 'perceptual' or 'actual' variables are chosen there is still a great deal of research to be done before all the issues involved can be resolved.

Allied to the necessity for further work on the identification of elemental attributes of LOS (e.g. separation of 'stopped' time from 'moving' time) and on the 'correct' specification of access modes, is a more general need to identify 'elemental' modes. That is, the seven different modes depicted in Fig 3 are, in a sense, arbitrarily defined, and are not necessarily the only set of alternatives perceived by Ballarat residents, nor is each alternative necessarily correctly identified. For instance, 'public transport' in Ballarat at the time of the survey consisted of trams and buses. As these modes were not supposed by regulation to compete for patronage, it seemed reasonable to *assume* them to be one mode for the sake of the modelling exercise. It is possible to remove any bias introduced by 'representing' more than one elemental alternative by a single alternative (Hensher 1979b), but there remains the problem that it is still up to analyst to define elemental alternatives. It is up to him to decide, for instance, if driving a car alone is different to driving one accompanied by passengers, or indeed, if driving with one passenger is different to driving with two (or any other number of) passengers.

One further area where plenty of research scope still exists is that of market segmentation. The dimension used in this exercise; licence/non-licence holding; was chosen arbitrarily, albeit with some prior knowledge. A more efficient method is, however, called for.

There are several possible, less arbitrary methods available for market segmentation. Perhaps the simplest is to test each potential segmentation dimension in turn with analysis-of-variance or similar technique, e.g. Automatic Interaction Detection (AID) - see Hensher 1976.

Another approach offerring some potential is to perform a factor analysis on the 'raw' socio-economic variables in order to determine the principal or underlying factors explaining travel behaviour. This approach has been tried in a slightly different travel context with a degree of success (Conroy 1978).

Perhaps the most appealing method yet proposed is that of using the utilities directly - the utility classification method (see Reid 1978).

Whichever method is chosen it is important to realise that in each modelling situation a separate market segmentation investigation will probably need to be undertaken. It is simply inefficient to choose a market segmentation schema without investigating the data first.

There is therefore still plenty of room for further improvements to the modelling procedure outlined earlier in the paper. Some of the suggested areas for improvement are generally applicable to any of the modelling approaches currently in use.

CONCLUSIONS

Although the exercise has not yet been completed (i.e. all the model stages depicted in Fig 3 have not yet been estimated) there are a number of tentative conclusions that can be drawn.

The exercise has clearly demonstrated that the strict specification of the utility function in terms solely of level-of-service (LOS) attributes, and in conjunction with market segmentation, can lead to meaningful modal choice models, particularly when careful selection of the estimation set and a sensible approach to choice set determination are adopted. Although this leads to a more complicated model structure, the increase in understanding that it brings makes it worthwhile. The resultant model should be particularly useful in the short term policy analysis context.

The essential message that emerges is that much thought should go into the selection of a model structure for each particular modelling task being undertaken. It is important to allow the data to help select model structure. 'Getting to know the data' is also important from the point of view of interpretation.

The hierarchical approach also seems to be superior to the simultaneous approach on the grounds both of theory (or at least intuitive reasoning) and practice. In fact, the way in which the exercise proceeded showed that model structure, market segmentation and choice set determination are not separate and independent issues at all, but are very much connected. Figure 3 clearly demonstrates this point and also the point that a rigid approach to modelling is inferior to a flexible one where the final model is arrived at by evolution rather than being pre-determined.

Nevertheless there are a number of drawbacks or limitations, either specific to the method proposed or generally applicable to other current modelling approaches as well, that require some resolution before the proposed method can reach its full potential as a predictive tool. These limitations are: the trade-off between a greater number of sub-models caused by market segmentation, an hierarchical structure and other partitioning of the data, and the increased number of observations therefore required to estimate the full model; the problem caused by multi-stage journeys (although current modelling practice does not tackle this problem at all); and the increased 'error' passed on by requiring yet more 'logsum' or 'inclusive price' terms. As well, the limitations it shares with other current approaches also bear further investigation, these being: functional form and the dilemma between 'perceptual' or 'actual' measures and finally the determination of the most efficient means of segmenting the travel market.

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