Asymmetric churn - academic jargon or a serious issue for transport planning?

1. Where did the concept originate?

The concept of an asymmetric pattern of churn was introduced by Phil Goodwin (Goodwin, 1999) at a lecture he gave to the Transport Planning Society.

"I would say that the only successful pathway to substantial change in transport behaviour at the aggregate level is by intervening to secure an 'asymmetric pattern of churn'. It means that we should stop talking in terms of encouraging people to stop driving and start using public transport – but seeking to increase a little the numbers of people who are already, every year, doing exactly that in huge numbers, and reducing a little the numbers of people who are already, every year, doing exactly the opposite, in equally huge numbers. Those are two quite separate decision processes, and they have to be targeted separately. The irony of it is that our standard models do not even recognise the existence of either group."

2. Purpose of this paper

This paper examines what is to be gained by recognising asymmetric patterns of churn in the methodologies used for assessment and forecasting in transport planning. After attempting to define what the concept means the paper considers the evidence for its existence and the scale of its importance. The paper then outlines the approaches used in conventional transport planning methodology. It highlights what aspects of travel behaviour are taken into account and what aspects are ignored. The implications of ignoring asymmetric churn are discussed indicating how this is likely to lead to unreliable results which provide too little information on the impacts of an intervention. Then methods used outside transport or in only limited use in transport are examined to see whether they could provide better methods of modelling travel demand.

3. Definition

It is helpful to start by defining precisely what is meant by an asymmetric pattern of churn. The Collins English Dictionary defines churn in terms of converting milk to butter, providing a helpful picture in the mind of milk in a metal container being shaken vigorously but only slowly changing its overall state. The analogy with travel behaviour is of many individuals being tempted and persuaded to change their behaviour by changes to their environment and circumstances but only slow and small apparent changes to the overall picture of behaviour. The Collins English Dictionary defines symmetry as "the independence of a property with respect to direction". In terms of travel behaviour, an asymmetric pattern of churn can be said to be gross changes in the travel behaviour of individuals that not being equal and opposite result in a net change in aggregate travel behaviour. Figure 1 illustrates the concept of asymmetric churn. It depicts seats on a bus service (nine seats are shown) and those occupying the seats at two different points in time. Three people are loyal users who are passengers at both points in time. Three people are lost between time t=1 and time t=2 and four people are gained, hence there is a net increase in patronage.

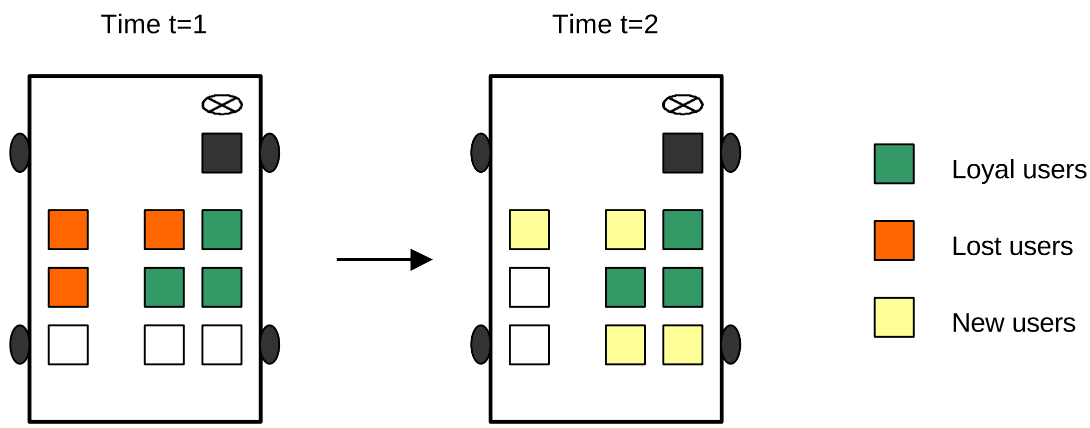

Figure 1: Asymmetric churn among passengers of a bus service

4. The empirical evidence

Before considering whether special attention should be given to asymmetric churn, it makes sense to see how significant it is. Starting with churn, we need to look at whether more gross change occurs than net change.

4.1 <u>Churn</u>

Cherrett (1998) used a number plate survey to investigate the day to day reappearance of vehicles for two routes into central Southampton between 0730 and 0915 for five consecutive weekdays. On average 27% of vehicles on any one day were unique to that day. The results were very similar at both sites and day to day variation in the number of unique vehicles was relatively small. In terms of vehicles reappearing on the next day, 49% of vehicles on one day reappeared on the next day with two thirds of these reappearing within the same five minute time interval or one of the five minute intervals either side of it. The result that only one half of vehicles appearing on one day reappear on the next day is the same as that found by Bonsall *et al.* (1984) in a survey of a commuter route in Leeds.

In contrast to the variability apparent for day to day traffic flow composition, Cherrett (1998) found that the total traffic flows were very stable from one day to another at each of the locations. Comparing 15 minute total traffic flows on the five days, the coefficient of variation (ratio of standard deviation to mean) varied from 0.027 to 0.073.

Bonsall *et al.* (1984) estimated based on their number plate survey and through reference to other data sources and analyses that for a sample of 100 commuters observed on a radial between 8.15 and 8.30 on a given weekday, a week later they would be doing as indicated in Table 1.

Table 1. Behaviour of 100 car commuters a week later

Behaviour a week later	Number
Drive past same point between 0815 and 0830	30
Drive past same point between 0715 and 0815	15
Drive past same point between 0830 and 0945	15
Drive past same point before 0715 or after 0945	7
Drive to the same destination by a different route	14
Make journey by another mode	8
Travel to a different destination	5
Stay at home	5
Sold their car	1

Studies looking at stability in behaviour over longer periods have also found substantial variability in individual behaviour. Goodwin (1988) looked at evidence on the stability of car ownership from a panel data set for the Netherlands. For 1984-1987, household car ownership reduced for 10% of individuals and increased for 11%. Examining the data it was found that 44% of two car owners reduced to one car but only 6% of one car owners reduced to zero cars. Goodwin (1988) examined the characteristics of car ownership reducers identifying that they were those with high initial levels of car ownership, higher than average public transport use and with particular personal circumstances.

Goodwin (1989) used the same panel data set to examine the stability of public transport use. Table 1 is a turnover table showing transitions in public transport use between non-users, low users (people who recorded 1 or 2 trips during the one week survey period) and high users (people who recorded 3 or more trips during the one week survey period).

Table 2. Turnover table for intensity of public transport use, 1984-87

	Individuals in 1987			
Individuals in 1984	Non-users	Low users	High users	Total
Non-users	1037	80	48	1165
Low users	91	35	17	143
High users	59	24	58	141
Total	1187	139	123	1449

The turnover table is a useful way of showing churn. In this case it can be seen from the column and row totals that there are quite small changes in the total users of each category between 1984 and 1987 but much larger numbers of users changing categories. The categories used here are quite broadly defined. If a more detailed aspect of behaviour was being considered then a greater amount of turnover would be expected. Examining the turnover table about the leading diagonal shows if the churn is symmetrical or not. In this case it is not quite symmetrical with a reduction in public transport users in each category over the period.

Watterson (1994) looked at dynamics in home and job locations in the Puget Sound region in Washington State. Panel survey data for 1989 and 1990 showed that 14% of households changed their residence location. The true figure is likely to be higher given the non-response of households lost to the panel. Moves were more likely for young adult households, lower income households and households that had experienced a change in household size, particularly a reduction. Most movers only moved within the same sub-region. Many households initially with long home-work journeys reduced their commute distance greatly by moving. On average movers reduced their home-work distances by 3.7 miles. The data also showed that 21% of continuing workers changed their work locations. 19% of these changed commuting mode as a result but there was very little net change in mode proportions. Considering those who had not changed home or work location one notable finding was that car sharing retention rates were only 40-50%.

4.2 Asymmetry

What about asymmetry of the churn? Asymmetry simply suggests that the underlying gross changes do not cancel out and there is net change. This is usually true. Table 2 shows an increase from 80.4% to 81.9% in the number of people who are non-users of public transport.

4.3 Causes of asymmetric churn

What are the reasons for churn? One explanation is offered by Dargay and Goodwin (2000) who found that long term elasticities of traffic with respect to travel ‘cost’ are larger than short term elasticities. The indication is that 50% of the adjustment to a cost change occurs within three years and 90% in five-ten years. Evidence also suggests that it takes five-ten years for behaviour to become wholly disassociated from its original state (five years for public transport use and ten years for car ownership). In other words it takes considerable time for people to fully adjust to changes that they experience. Another explanation is offered by Goodwin (1989) from the Netherlands panel data sets which indicate that changes in individual behaviour are larger for people whose circumstances change (in terms of life-cycle stage, employment status and income).

What are the reasons for asymmetry? A trend in an underlying factor will cause more people to change their behaviour in one way than another. A relative increase in public transport fares will cause more people to reduce public transport use than to increase public transport use. Another reason for asymmetry is that even if an equal number of people experience a change of one kind as the opposite kind (say, a reduction and increase in income) the responses to these changes may not be equivalent and opposite. Dargay and Goodwin (2000) found evidence for non-reversibility in the effect of prices on car ownership and use.

In summary, there are four underlying reasons why change in travel behaviour over time can be characterised as an asymmetric pattern of churn:

1. Life event changes - the population’s circumstances are continually changing for non-transport reasons (for example, due to changes in job and family circumstances). These have a major impact on travel decisions.
2. Delayed and discontinuous responses - people do not always adjust to a change to their circumstances or their environment immediately but over a period of time and/or after a period needed to be aware of the change. Their response may occur in a series of changes to

behaviour and not just in one transition of behaviour. (It is also possible that people change their behaviour in advance of an intervention in anticipation of it.) People may also respond little or not at all to a small change in their circumstances or environment but substantially to a larger change (i.e. with 'stickiness').

3. Non-reversibility - people will not necessarily respond in the equivalent but opposite way to a change of the same magnitude in one direction as the other direction.
4. Routine variability – the routine travel behaviour of individuals varies more than assumed.

One other question of interest is whether churn is increasing in importance. A National Association of Pension Funds report found that school leavers will have an average of 11 jobs over their lifetime compared to todays retirees who average seven (Collinson, 1999). In Spring 1999, approximately 1.2 million people worked from home in the UK at least one day per week in their main job using a computer and a telephone link to the employer or client. A year later, this had increased to 1.5 million, representing 5.5% of those in employment (Huws, 2000). This form of employment is likely to be associated with less stable travel patterns. In 1998/9 almost 2.4 million households had moved within the previous year, about 12 per cent of all households. Like other Western countries, contemporary Britain has recently experienced major demographic changes that have important repercussions for migration behaviour. These include decreasing fertility, increasing life expectancy, and increases in marital break-up and re-marriage. Progression through the life-course has become more variable between individuals, and for many may now include several different episodes of household formation and dissolution involving different partners, each of which is likely to involve residential mobility for at least one household member.

4.4 Implications of asymmetric churn

Having demonstrated that asymmetric patterns of churn are a natural phenomenon of travel behaviour there are implications both for policy and the assessment of policy. In the opening paragraph of the paper Phil Goodwin notes that at any time there are people changing their behaviour in a favourable way as well as an unfavourable way. The reasons for changes in either direction need to be understood and interventions made to secure more movement in favourable ways. Goodwin (1988) has analysed the characteristics of individuals in car reducing households and finds that people with high public transport use are more likely to reduce car ownership and that the level of public transport use required to cause car ownership reduction appears to be greater when public transport is less attractive. Goodwin (1989) has suggested that maintaining existing public transport users depends on retaining of people whose lives are stable and gaining new users depends on attracting people whose lives are changing.

Fergusson *et al.* (1999) in their report looking at lessons from the health sector for travel behaviour identified a process of changing travel behaviour which recognises different stages of behavioural change - pre-contemplation, contemplation, preparation, action and maintenance. They recognise the importance of major life events as offering stimulii for changing travel behaviour. These offer an opportunity to intervene to move people through the process of change. They discuss some examples of life events and the actors and methods that can be used to influence behavioural change.

5. Transport planning methodology

The paper now concentrates on assessment and forecasting methodology which is the main focus of the paper. A brief summary of the main principles of current transport planning methodology is given noting the assumptions made about travel behaviour.

5.1 Elasticity values

A simple approach to assess the effect of an intervention is to use elasticity values forecasting the change in travel demand per unit change in travel cost/time (referred to as generalised cost) introduced by the intervention. One limitation of this procedure is that the new level of travel demand forecasted might itself result in modified generalised costs. Thus the travel demand will not be consistent with the new generalised costs. Another limitation of this procedure is that it does not tell us anything about redistribution of travel demand spatially or temporally.

5.2 Four–stage models

The four-stage model is designed to tackle these limitations (see Figure 2). Information about the urban activity system (population, land use and transport networks and services) is used as input to the model. The study area is divided into zones. First, the model predicts the trips generated for each zone. Second, the model predicts the pattern of trips between zones (trip matrix). Third, the model allocates the trips between different modes (mode-specific trip matrix). Fourth, the model assigns the trips to the transport network. An iterative loop is used to ensure the generalised costs predicted in the assignment stage are consistent with route choices and perhaps the travel choices implied in the modal split and trip distribution stages. In this way the model attempts to provide a user equilibrium solution where no traveller is able to reduce their generalised costs by making a different choice to the one that they are making. This is an ‘end state’ stable pattern of behaviour which has settled down to reflect past changes to the system.

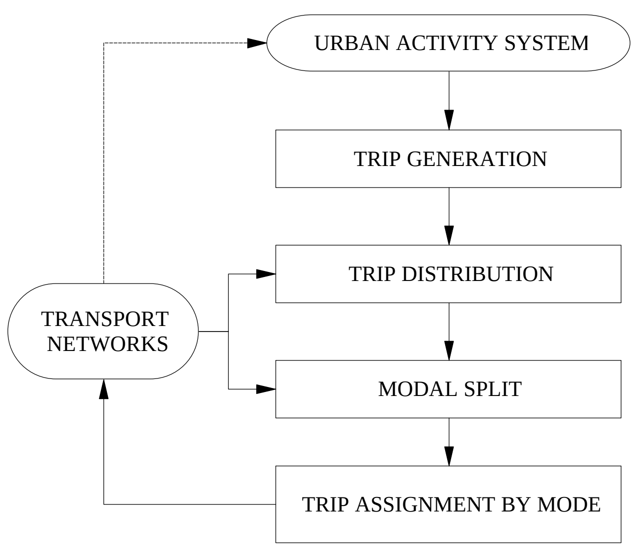

Figure 2: Four-stage model

The parameters in the model are normally estimated using cross-sectional data from a survey undertaken at a single point in time (a one-shot survey). The data collected describes the characteristics of a sample of trip makers and their travel choices. It also measures the generalised costs of travel using different modes. Sensitivity of behaviour to explanatory variables is therefore estimated based on the variation in behaviour within the sample. The model is calibrated for the base-case situation by attempting to set the model parameter values so that predicted travel choices most nearly match observed travel choices. Forecasts are made for future scenarios by setting the values of explanatory variables (e.g. in-vehicle time, public transport fares) to represent the scenarios under consideration.

Various ways of increasing the sophistication of the modelling approach outlined above have been developed. These include congested traffic assignment models, representation of travel in terms of tours instead of trips and incorporation of time of day choice. The equilibrium principle, however, remains fundamental to the model approach.

5.3 Discrete choice models

To illustrate the model estimation process used within the four-stage model consider the example of the modal split model presented in McFadden (2000). The work trip mode choice model was estimated using data on individuals collected in 1972 in the Bay Area, San Francisco for the following four alternatives:

1. Car alone.
2. Bus with walk access.
3. Bus with car access.
4. Car pool.

A discrete choice model (of the type multinomial logit) was specified and estimated which predicts the probability of using the alternatives based on the following attributes of the alternatives and characteristics of the individuals:

1. Cost divided by income
2. In-vehicle time
3. Walk time
4. Transfer time
5. Number of transfers
6. Bus headway
7. Family income
8. Number of persons in household who can drive
9. Commuter household head or not
10. Employment density at workplace location
11. Home location in or near CBD
12. Cars per driver
13. Alternative specific dummy

The principle underlying the discrete choice model is random utility maximisation. An individual is assumed to select the option from a set of alternatives which maximises their net personal utility. The model is specified with each alternative having a utility comprising of a deterministic component which is a function of the attributes of the alternative and characteristics of the individual and an additive random component to reflect unknown or unmeasurable quantities of the utility function.

After the introduction of the Bay Area Rapid Transit (BART) the capability of the model was put to the test by comparing predicted mode shares with observed mode shares. The new BART mode (train) was added to the list of alternatives and 1975 travel times and costs collected. The model predicted BART share of 6.4% compared to an actual share of 6.2%. It predicted car alone share of 55.8% compared to an actual share of 59.9%. It predicted bus share of 14.9% compared to an actual share of 12.2% and it predicted car pool share of 22.9% compared to an actual share of 21.7%. The total number of correct predictions of mode choice for the sample of 631 was only 53.9%, however.

5.4 Incremental models

Instead of calibrating a base-line model of travel demand, an incremental model takes an externally supplied trip matrix assumed to be in equilibrium. The model predicts the changes to travel choices that would occur relative to the base-line trip matrix given changes in generalised costs. Travel choices are represented as a nested system of discrete choice models. The predicted travel choices are assigned to the transport network, generalised costs updated, travel choices re-calculated and the process continued until equilibrium is reached. This approach is used by strategic models which seek to provide broad-brush indications of the relative effects of policy measures and scenarios. Strategic models use very few zones and often a simple supply model instead of an assignment model.

5.5 Variable trip matrix methods

Simpler methods of predicting demand have been used in conjunction with assignment models. One method is the elastic user equilibrium assignment method which adjusts the trip matrix on a zone-to-zone basis based on changes to generalised costs predicted by the assignment model. It requires elasticity values for the sensitivity of demand with respect to cost. Of course this does not tell us in what way demand changes, only by how much demand to use the transport network changes.

5.6 Land use-transport interaction models

Land use-transport models have been developed as a tool for long term regional planning. They forecast changes in transport demand, accessibility and land use activity for time steps measured in years. The pattern of travel between zones is a function of the economic interactions between land use activities and changes in the spatial pattern of land use are predicted partly as a function of accessibility. For each time step modelled an equilibrium solution is sought between travel demand and generalised costs in the same way as the four-stage model. Unlike the methods previously mentioned though, the model is dynamic in that circumstances in one time step cause a change to circumstances in the next time step (through accessibility influencing the future land use decisions of various actors). Thereby it models a process of change.

5.7 Micro-simulation

Micro-simulation attempts to represent in a realistic manner the way in which individuals interact with each other and their environment. The most common application in transport is simulating the effect of traffic management measures on network operational performance. Our main interest though lies with travel demand models. The Dutch National Model System (NMS) simulates the behaviour of a sample of households and individuals using standard discrete choice models (Gunn and Ben Akiva, 1993). First, a 'prototypical' sample of households is established. Second, the number of driving licences within each household is predicted based on cross-sectional data but adjusted against aggregate licence-holding projections which contain trend effects not captured in the cross-sectional models. Third, the number of cars owned by each household is predicted. Fourth, trip frequency, mode and destination for each person are predicted. Fifth, the time of day of a trip is predicted based on stated preference data and trips are then assigned. An equilibrium solution is sought between time of day choice and generalised costs predicted by the assignment model. Although the model simulates the decisions of the 'prototypical' sample the decisions are based mainly on cross-sectional data and the model is used to predict an 'end state' resulting from a particular policy measure rather than the process of change.

5.8 Models for car ownership and use

Different methods have been applied to this area of analysis as reported by Dargay and Goodwin (2000). The 1997 UK National Road Traffic Forecasts used separate aggregate models for car ownership and car use based on a combination of cross-section household analysis and non-lagged time series analysis. The car ownership model has explanatory variables for household demographic structure and income but not for cost of car purchase or use. In the car use model the elasticity of mileage per car with respect to fuel cost is –0.13. Studies using aggregate time-series methods with lag structures (this assumes the impact of a cost change is distributed over a period of time after the change with the period empirically determined) have found, however, that car ownership, car use and public transport use are all sensitive to costs with adjustment periods of up to ten years.

A pseudo-panel study using independent samples of cross-sectional data tracing cohorts (groupings of similar individuals) and specifying a model for average cohort car ownership found that there were (i) generational effects not explained by income, (ii) elasticities with respect to rising incomes are higher than for falling incomes, (iii) costs have substantial effect, (iv) adjustment takes up to ten years with elasticities twice as great in the long run as the short run, and (v) elasticities differ between different household types (e.g. urban and rural). This indicates models estimated on cross-sectional data may give unreliable results.

5.9 Stated preference techniques

An alternative to using cross-sectional (revealed behaviour) data to estimate models is to use stated preference survey techniques. This enables the model developer to investigate responses to experimentally controlled hypothetical situations. If subjects of these surveys are able to make realistic judgements of how they would adapt to different situations then it is possible that better predicting models could be estimated than models using cross-sectional data.

Models specified on cross-sectional data tell us about differences in behaviour between individuals of different characteristics at a set point in time. With stated preference data the same individual is being sampled at least twice, once for the existing situation and further times for the hypothetical situations. An interesting question is the time-scale in which subjects are assumed to consider a possible change in behaviour. Is it the day they are surveyed, a week later or sometime further in the future? The model developer will usually assume immediately after the hypothetical situation is put in place. The survey, however, could be designed to ask subjects how they would react over time to the intervention and attempt to capture the process of change and subsequently model it dynamically. This though is a demanding expectation.

6. Why taking account of asymmetric churn is important

All models are a simplification of reality. But is there anything about the procedures used currently by practitioners, which take no account of asymmetric patterns of churn and instead assume transition from one stable pattern of behaviour to another (via equilibrium solutions based on maximisation of utility), that makes us believe that they will not provide the assessments and forecasts that we require. There are, in fact, a number of reasons for suspecting this:

1. The models do not explain the process of behavioural change well as their specification fails to capture travellers' decision making processes and the nature of the factors that influence the processes.
2. When assessing the possible impact of an intervention it is usually assumed that there will be no change in behaviour in the 'do nothing' scenario. Asymmetric churn suggests that there is systematic change in the system due to long term adjustments to past occurrences and life event changes. Cairns *et al.* (1998) point out that an understanding is needed of the changes that would occur anyway without the intervention and it is not sufficient to assume that no change would have occurred without the intervention.
3. What we want from models is changing. We now want to know about the experience of different individuals over time and not just at a non-specific future date. For example, it is of concern to elected officials to know if there will be a time when a group of the community will suffer adjustment problems as a result of an intervention. Furthermore, discounting calculations require accurate forecasts of travel behaviour at successive time points.
4. The interventions that require assessment will include those that acknowledge churn and use it to its advantage. For example, Fergusson *et al.* (1999) suggests intervening at the time of life events to try to change people's travel behaviour. For these interventions, recognition of churn is essential to enable any assessment.

If it is felt that the last three issues are important then the first issue must be addressed. The paper now considers the reliability of forecasts made if models are not specified to account for asymmetric churn. It considers these from the points of view of the four causes of asymmetric churn identified earlier: life event changes; delayed and discontinuous responses; non-reversibility; routine variability. Before doing this, it is helpful to summarise well known limitations of cross-sectional analysis (Davies and Dale, 1994).

- cross-section data does not provide information on the process of change. One way this is evident is that the data tells us about differences in behaviour among age groups but the effects on behaviour of aging and cohort effects are indistinguishable. For example, the current car use of older age groups will not be repeated in future years as people joining these groups will have been more used to using cars during their life-time than the previous members of the age group.
- cross-section data does not represent inertia effects – responses to a change in the environment may not be immediate as it takes time to realise change has taken place and to be in a position to change behaviour. Furthermore, current behaviour tends to be conditioned on past behaviour. The response to a change in circumstance or environment may depend on the amount of time the current behaviour has been carried out (the longer this is perhaps the greater difficulty in modifying it as many aspects of a person's life are aligned towards the behaviour, this is temporal dependence) and the types of behaviour in the past (if other types of behaviour have been tried in the past then there be more willingness to try them again, this is state dependence). The opposite effect is possible though. Through time the dissatisfaction with current behaviour may gradually increase and relatively little incentive be required to tip the balance in favour of a change in behaviour.
- cross-sectional analysis does not account for omitted effects – there are always unknown factors which if they are correlated with one of the explanatory variables lead to mis-specification of the model. The effect of explanatory variables will be over-estimated if omitted factors are not taken into account. The earlier example for the BART mode choice model showed the tendency for cross-sectional based models to underpredict the continued use of a dominant alternative. Also it is to be noted that if an attempt is made to account for inertial effects in a cross-sectional analysis through including a variable representing past behaviour then the variable's effect is likely to be over-estimated as it will be correlated with omitted effects.

Hagenaars (1990) points out that by using cross-sectional data to infer process of change the assumption is made that changes in travel behaviour and the qualities of different travel options over time are related to each other in the same way as the cross-sectional differences in these variables. This requires the system of variables under study to be in equilibrium. Even if this is true the estimated model will not provide any information on how long will be taken to reach a new equilibrium if travel circumstances change. Davies (1994) remarks that cross-sectional analyses will reflect the cumulative effect of changes to the explanatory variables (and omitted effects) in the past. They will not reflect, as is supposed, how the current level of the explanatory variables, attenuated by inertia, influences behaviour.

6.1 Life event changes

When models are applied it is either assumed that the population of the study area is constant (for the base case and after an intervention made) or simple estimates are made for population growth. This can be justified by arguing that there will not be substantial net change in the characteristics of the population in the time period under consideration even if there is gross change (e.g. individuals enter and leave the study area).

The evidence discussed earlier, for example of Goodwin (1989), however, suggests that a change in travel behaviour is often triggered by a life event. If these are not recognised in cross-sectional models the models will be biased if the omitted variables (life events) are correlated with explanatory variables included in the model. It is quite likely for there to be a correlation between the socio-economic characteristics of individuals and the probability of certain types of important life events occurring.

Models estimated from cross-sectional data reflect average differences between different population groups without reflecting the amount of change that occurs in reality due to uncaptured factors such as life events. If the different types of change were modelled separately (say, those that switch from public transport to car and those that switch the other way) then it can be hoped that a more precise estimate of net change can be obtained as the difference between two separate estimates. The factors causing the two different changes in behaviour are likely to be quite different. Such an approach requires repeated data for the same individuals so that the factors influencing a change from one state to another can be analysed.

In section 7, examples are described of the use of micro-simulation to explicitly model life event changes as part of forecasting travel demand. The forecasts of these models are compared to real data and forecasts from other models with the results suggesting that they perform better. This indicates that greater predictive capability and reliability is likely to be achieved through an explicit representation of life event changes.

6.2 Delayed and discontinuous responses

Goodwin (1998) has examined the implications of behavioural responses occurring gradually and after a period of time rather than immediately after an intervention. He noted that at any time the population studied is likely to be in disequilibrium with people adjusting to past changes. These will include changes in personal circumstances, which are likely to be different for different people but undergoing an overall trend, and changes to environmental conditions, which are likely to have moved in the same way for all the population. There is no reason to suppose that these can be treated as random compensating errors as assumed in cross-sectional analysis. This is illustrated by the evidence from a South Yorkshire panel study which shows that cross-sectional differences in car ownership between income groups are strong and symmetrical while differences within individuals as they changed income group during a three year period are weak and non-symmetrical.

Goodwin (1998) suggested there are two possible situations with cross-sectional analysis. In the unlikely event the system was in equilibrium when the data was obtained then an estimated model can predict the equilibrium state of an intervention. It cannot tell us when that will happen. In the event the system was not in equilibrium when the data was obtained then an estimated model will not be able to predict the equilibrium state of an intervention. It can only tell us an interim state the system might reach. Goodwin (1998) noted that in calculating the present value of a scheme the error depends on the difference between the static elasticity used (a single value) and the true dynamic elasticity (which is a time-dependent function), the speed of adjustment to equilibrium, the discount rate and the time horizon used. Using a long run elasticity will result in over-estimated benefits of price decreases and under-estimated losses of price increases. The opposite is true for using a short run elasticity.

In the same paper, Goodwin (1998) also presented the findings of a simulation experiment for travellers choosing between two modes on the basis of the travel time difference and the travel cost difference between the two modes. Random values are generated for the travel time and cost differences and for individual marginal utilities of time and money and habit thresholds. A base case is established for each individual where mode choice is deterministic. Then a trend in times or costs is applied to each individual for subsequent passes. As a result of the habit threshold some travellers will appear to be choosing the more expensive mode in subsequent passes. The actual values of time for the sample are known (these are the relative marginal utilities of time and money used in the simulation) and an average for the population can be calculated. This is compared to the value estimated from the simulation results based on a cross-sectional analysis. The results showed that the value of time is over-estimated for money cost change and under-estimated for travel time change. The findings suggest that if there exist thresholds for behavioural change then cross-sectional analysis will produce biased estimates and if there are delayed responses then cross-sectional analysis will produce biased estimates if time is not allowed for people to respond fully.

Goodwin (1998) has presented a strong case for systematic errors being introduced by ignoring the fact that changes in behaviour are gradual (or what is often referred to as lagged) rather than immediate. There is also the implication with delayed responses that current behaviour is dependent on past behaviour which brings into contention another reason why cross-sectional models are mis-specified. This is perhaps a cause of churn rather than one of its essential properties but as a cause it is something that will need to be dealt with to enable reliable forecasts of travel behaviour to be made.

6.3 Non-reversibility

A relative change of utility in opposite directions is usually assumed to result in an equal and opposite change in the probability of undertaking some form of behavior. If this assumption does not hold and change in behaviour depends on direction then the model is mis-specified and biased predictions will occur dependent on the precise nature of the relative change in utility. As a demonstration of the importance of this, Goodwin (1998) found evidence that people are more likely to increase car ownership after an increase in income than they are to decrease ownership after the same decrease in income.

6.4 Routine variability

Models are generally developed based on cross-sectional data captured from surveys asking people about their travel behaviour on a specific day. It has been discussed earlier though how few people's behaviour is consistent from one day to another or even one week to another. The consequence is that an artificial degree of stability is assumed to be prevalent. Using information for one day to estimate average trip frequencies may enable a model to estimate the overall number of trips made in an area quite accurately but it will not reflect the fact that one week a particular individual is making more trips than usual and another individual is making less trips than usual. Massot *et al.* (2000) have emphasised the value of conducting surveys which ask people about their monthly trip making instead of their trip making for one day. They point out that this allows us to look at the distributions/variation of travel behaviour.

Ignoring the natural variability of travel behaviour could lead to unreliable models. An individual who uses a variety of modes can be expected to be more likely to change their behaviour after an intervention than an individual who uses one or two modes only. This would not be represented in models estimated on the type of data generally used at present.

7. Treatment of asymmetric churn

The paper now looks at possible ways of recognising asymmetric churn in transport planning assessment methodology by reviewing statistical methods used in other fields and some modelling approaches proposed in transport.

A literature search found churn mentioned in the following contexts:

- in telecommunications, subscriber churn is used to refer to customers changing their service provider;
- in financial markets, investment managers are said to have an incentive to churn the market where they can profit at the expense of investors as a result of asymmetric information. This exists where investment managers and investors have different information on asset values;
- in economics, fiscal churning is a measure of the amount by which citizens pay taxes and receive transfers. There is a high degree of fiscal churning when a large amount of tax is collected and then recycled back to citizens;
- in employment, churning flows are defined as the difference between a company's gross worker flows and gross job flows (i.e. churning flows are high when staff turnover is high but staff posts are stable); and
- in migration, geographical churning is a measure of the amount of movement of people from one residential location to another.

Methods of dealing with churn from this literature appeared to be of limited value though. They usually focussed on aggregate measures of change. As an example, Greis and Zachary Gilstein (1991) compared two statistical methods of forecasting levels of churn (disconnect and subsequent reconnects which do not contribute to growth) at individual telecommunication exchanges. The methods were time-series models forecasting churn based on trends for the exchange under consideration and an empirical Bayes method forecasting churn based on trends for the exchange under consideration and the larger population of exchanges. These methods do not attempt to determine the underlying reasons for churn. What proved to be more worthwhile than this literature were casebooks of the statistical methods used in analysing social and political change (Dale and Davies, 1994; Hagenaars, 1990).

7.1 <u>Statistical data and methods</u>

Earlier the limitations of using one-shot, cross-sectional data to infer future change were highlighted. Other types of data are listed below followed by methods to analyse them:

1. Cross-sectional data observed at a series of discrete time points for different individuals/cases, either observed at the individual level or for individuals aggregated across categories.

2. Aggregate time-series data: a single measure for a dependent variable or set of dependent variables at a series of discrete time points.
3. Cross-sectional data repeated at a series of discrete time points for the same individuals/cases, either obtained through a retrospective study asking individuals about past history, through a panel study collecting information for a representative sample of the population or through a cohort study collecting information for a particular population sub-set.
4. Data recorded in continuous time indicating the timing of different events.

Trend analysis

Sometimes surveys of individuals are repeated at regular intervals. Different individuals are sampled for each survey so it is impossible to directly analyse churn. The main two anticipated advantages of using repeated cross-sectional data are an increased sample size (for a random sample the standard errors should be proportional to the square root of the sample size) and using data over a period of time introduces more variation in the explanatory variables which enables more precise estimates to be made of the effect of the variables as long as their effects are not changing over time. The latter assumption might be rejected if travellers and their environment are experiencing an overall change in their characteristics which will result in different responsiveness in behaviour over time.

Repeated cross-sectional data also allows us to explore if there is any trend in time in addition to that captured from the explanatory variables. This can be informative about the stability of behaviour but it should be recognised that survey period specific effects may include a part which is actually lagged effects of events occurring in the past. Repeated cross-sectional data can be used to examine the separate contribution to aggregate change in behavioural response which is due to changing behaviour and due to changing population in a method called growth accounting (Micklewright, 1994). The method applied to mode choice data collected annually would be as follows:

1. Estimate separate model for each year's data.
2. Apply coefficients for each year to each other year to build up a matrix of mode choice estimates.
3. Examine how the fixed population for a particular year is predicted to change its mode choices in subsequent years using the coefficients for those years. This indicates the impact of changing behaviour.
4. Examine how changes to the population are predicted to influence mode choices by using the coefficients for one year with subsequent year's data. This indicates the impact of changing population characteristics.
5. This way the causes of aggregate change can be decomposed into a changing behaviour component and a changing population component.

It is important to note that this technique can only tell us about the effect of net changes to population characteristics and net changes to behaviour (as it is based on cross-sectional models). It does not account for delayed responses or the effect of life events. It can, however, be used to diagnose whether changing behaviour is a substantial cause of aggregate change in behaviour over time. If so, this suggests that change over time cannot be explained well by cross-sectional data and that longitudinal data is required to understand the underlying process of change.

Data pooled from a series of surveys at different time points can also be used to create a ‘pseudo-panel’ (Micklewright, 1994). Whilst different individuals are sampled at each time point individuals from the same sub-population are sampled at each survey who might be expected to change their behaviour in the same way. This can go same way to telling us the process of change undergone by sub-groups. This approach is of limited value, however, in addressing churn as the initial characteristics of individuals and life events experienced by individuals vary so much that it will be impossible to capture this and analyse it using a ‘pseudo-panel’.

Lagged models

Lagged models have been widely applied, especially in econometrics, to aggregate-level, time-series data, where the dependent variable has a single measure. Aggregate data of course is unable to tell us about the churn of individuals between time points. Lagged models are specified so that the dependent variable at y_t is explained either by:

- dependent variable itself at previous time points (y_{t-1}, y_{t-2}, …) - resulting in a lagged endogeneous model;
- explanatory variables at previous time points ($x_{i,\, t-1}$, $x_{i,\, t-2}$, …) - resulting in a lagged exogeneous model.

Including y_{t-k} as an explanatory variable tends to prevent ‘real’ explanation of y_t but can improve forecasting capabilities. Car ownership models have been developed using time-series data and incorporating lagged effects for explanatory variables such as fuel price (Dargay and Goodwin, 2000).

Gallet and Agarwal (1999) examined the effect of health information scares on US cigarette demand. They used what they termed a gradual switching model which recognises that impacts are not immediate. The model assumed demand in a given year, C_t, is dependent on the price of cigarettes, P_t, disposable income per capita, I_t, advertising per capita, A_t, and demand in the previous year, C_{t-1}. The demand intercept and elasticities are specified in a way that they can change over time. This is enabled by introducing a linear transition path between two empirically determined time points, which allows the effect of the explanatory variables to adjust over time.

$$C_t = (b_0 + l_t d_0) + (b_1 + l_t d_1)P_t + (b_2 + l_t d_2)I_t + (b_3 + l_t d_3)A_t + b_4 C_{t-1} \qquad (1)$$

where $\bullet_t = 0$ ($t<t_1^*$), $\bullet_t = a_0+a_1 t$ (for $t_1^* \leq t_2^*$), $\bullet_t = 1$ (for $t> t_2^*$)

For the data investigated, the model showed that the nature of cigarette demand changed between 1961 and 1971 when it declined dramatically. The price elasticity and advertising elasticity decreased in this period also. The authors note that combining this analysis with analysis of cross-sectional data for individuals can show the contribution of a changing composition of the market (in terms of types of smokers) on cigarette demand.

Individual-level data from panel (or cohort) surveys can also be analysed using lagged models where measures from previous time points are included as explanatory variables to take account of the influence of past history (Davies and Dale, 1994). To take account of the fact that observations at a series of time points for the same individual are not independent an individual-specific error term is included in the model. This also has the benefit of enabling the effect of omitted variables to be controlled at least as far as they are invariant for individuals. It is important to note that specifying a model with explanatory variables that describe a person's history (e.g. their state at a previous time point or how long ago something happened) but not including an individual-specific error term is not a sufficient condition to reliably analyse change and the factors influencing it.

Davies and Dale (1994) illustrate the benefits of the above method for analysing the employment status of married women and the effect of their husband's employment status. They first specify a cross-sectional model for wife's employment status (logistic regression model) with explanatory variables such as husband's employment status, wife'a age and wife's qualifications. This explains 18% of the 45% shortfall in the employment of wives with unemployed husbands compared to wives with employed husbands. A longitudinal model with an individual-specific error term, controlling for omitted variables, reduces the shortfall by 6%. Including in the longitudinal model a dummy variable taking the value 1 if the wife is in paid employment during the previous month and zero otherwise (called a Markov component) results in a greatly improved model fit and further reduces the shortfall by 2%.

Davies and Dale (1994) also use the data to show that including an explanatory variable of the current number of years out of employment (retrospective information) leads to quite different results depending on whether a cross-sectional method or longitudinal method is used. In the former case the implication is that increasing years out of employment decreases probability of being employed but in the latter case it is not significant. This indicates that it is a spurious effect in the former model as it reflects the effect of omitted variables which mean that unemployed wives that have been out of employment for a long time are over-represented in the sample (a natural sampling phenomenon).

Multi-level models

Multi-level modelling (or variance components modelling) is a method of recognising that a data set may have natural clustering. Using individual-level specific error terms is one way of dealing with this as it recognises measures over time for an individual constitute a natural cluster. Multi-level models provide a more general framework allowing more powerful treatment of cluster effects (Plewis, 1994). It allows different relationships to apply to different clusters.

The way the model is formulated might be as follows for the example of number of trips made per month by an individual which is thought to be clustered according to their life cycle stage. At level 1 (bottom level) which would apply to individuals the number of trips y is expressed as a function of explanatory variables x.

$$y_{ij} = b_{0j} + b_{1j} x_{1ij} + b_{2j} x_{2ij} + e_{ij} \qquad (2)$$

where
e represents unexplained variation;
i is the level 1 subscript applying to individuals;
j is the level 2 subscript applying to life cycle stage.

The use of subscript j for each of the coefficients indicates that the value of the coefficient can vary for different life cycle stages. Variation in the coefficients can try to be accounted for by life cycle stage variables z.

$$b_{oj} = g_{00} + g_{01} z_{1j} + u_{0j} \qquad (3)$$

with similar equations possible for the other two coefficients, ✍$_{1j}$ and ✍$_{2j}$.

By using panel data the multi-level model can explore how the measured behaviour at a later time is influenced by previous history within a multi-level framework. Plewis (1994) illustrate this with the example of pupil test scores. In a two-level model, pupil test scores are related to previous test scores and curriculum coverage at level 1 (bottom level) with between teacher curriculum coverage related to mean class previous test scores at level 2 (top level). This was used to examine if there were between-teacher differences in progress and what might explain this.

Multi-level modelling can also be used to examine how stable behaviour is over time (Plewis *et al.*, 1990). The time spent on an activity by individuals can be examined at two levels with level 1 representing between-day variation (using data for different days) and level 2 representing between-individual variation (using averages for each individual). This allows the routine variability of behaviour to be represented. It requires data to be collected over a period of time as recommended by Massot *et al.* (2000).

It should be pointed out that multi-level models are quite different to nested models, which are often used in modelling travel behaviour. A nested system of discrete choice models might be used to simultaneously model two choices, for example, destination choice and mode choice. Multi-level models deal with the situation where a single dependent variable is influenced by attributes at different levels.

Markov models

Markov models provide a method of analysing a sequence of outcomes or what is referred to as Markov chains (Langeheine and van de Pol, 1994). They are suited to situations when the main interest is in the dependence of current behaviour on previous behaviour, rather than the underlying reasons for the behaviour in the first place. This might apply to the choice of mode at a series of time points (see the illustration in Table 3). It is often applied for discrete panel data on attitudes, voting intentions, employment status or brand choice.

Table 3: Contingency table of mode choice data

Time			Observed frequencies
T=1	T=2	T=3	
1	1	1	43
1	1	2	5
1	2	1	3
1	2	2	7
2	1	1	12
2	1	2	1
2	2	1	10
2	2	2	25

Categories: 1 - car, 2 - public transport

Markov models involve transition matrices which give transition probabilities (the conditional probabilities of a change from one state to another state). Equation 4 is an example of a transition matrix which indicates that the proportion of those who use the car at time t=1 who also use the car at time t=2 is 0.85 and the proportion who switch to bus is 0.15. The proportion of those who use the bus at time t=1 who also use the bus at time t=2 is 0.53 and the proportion who switch to car is 0.47.

$$\hat{T}^{21} = \begin{bmatrix} 0.85 & 0.15 \\ 0.47 & 0.53 \end{bmatrix} \qquad (4)$$

Various assumptions can be made and relaxed when using Markov models:

- Markov chain is stationary (i.e. the transition matrices are unchanging over time);
- Markov chain is first order (i.e. the state at time t is sufficiently explained by the state at time t-1);
- there is only one Markov chain (i.e. there could be more than one chain each having its own initial probabilities and transition probabilities);
- Markov chain applies to the whole population (i.e. different chains could apply to different subgroups of the population);
- there is no measurement error in the data.

Allowing measurement error and using a Markov latent model is found to be useful as otherwise stability of behaviour tends to be underestimated and change overestimated. The effect of exogeneous, explanatory variables can be analysed by examining their effect on individual Markov chains (i.e. the probabilities in the transition matrix).

Markov models can be used to identify the limiting distribution of the states being analysed (e.g. the mode choices after a settling down process in response to an intervention). This is determined by application of the transition matrices until the distribution is very nearly the same at one time period as the previous time period. This can be considered to be when equilibrium is reached. This application of Markov models raises the question of whether it is possible to identify an initial state before the intervention when the system is in equilibrium.

Event history analysis

Event history analysis is applied to data recorded in continuous time indicating the timing of different events. Hazard models are a popular method of event history analysis. They estimate the 'survival' time before the event of interest ('hazard') occurs and the effect of independent variables on this (Tuma, 1994). These models use the hazard rate which measures the probability that an event occurs at time t, conditional on it not having occurred before t. The proportional hazard formulation is often used in event history analysis. The effect of explanatory variables is examined by assuming the hazard rate is a function of the explanatory variables multiplied by the time-varying base-line hazard rate h(t). Behaviour that may be modelled this way is the duration of activities such as living at a residence or visiting a destination.

If we are interested in both the timing of events and the sequence of events these can be modelled separately using hazard models for the former and Markov models for the latter. The timing of events may, however, be influenced by what the previous events(s) were or the next event may be influenced by the duration in the current event or past event(s). Markov renewal models (Kitamura, 2000) can be used in this case. These estimate the probability of a future state *j* occurring at time t given an initial state *i* based on a function including a Markov transition component and a survival function component.

Summary

Table 4 summarises the statistical methods that have been reviewed and their possible role in the context of asymmetric churn. Lagged models predict behaviour taking account of past history. They therefore provide a means of modelling the dynamics of behaviour, including life event changes and delayed and discontinuous responses. Multi-level, lagged models allow the routine variability of behaviour to be explicitly represented. Markov models offer a way of analysing patterns of transition of behaviour. They can be used to separately look at, say, the probability of changing mode from car to bus and bus to car instead of assuming the same factors are involved. Hazard models allows a continuous time dimension to be used which can explicitly represent the fact that behavioural responses are not instantaneous and continuous. Markov models and hazard models can be combined to allow both behavioral states and durations to be considered.

7.2 <u>Modelling approaches</u>

Alternatives to the equilibrium approach of modelling travel behaviour responses have been proposed. These are reviewed and their value in addressing asymmetric churn is discussed.

Evolutionary models

Levinson (1995) has proposed an evolutionary modelling approach as an alternative to equilibrium modelling. One of the arguments put forward in favour of evolutionary modelling is that equilibrium models operate with a negative feedback loop where more demand increases congestion which leads to less demand. In many respects travel demand operates with a positive feedback loop where increased demand encourages developments leading to more demand.

Table 4: Statistical methods and their application

Method	Data used	Dependent variable	Application	Limitations
Trend analysis	Cross-sectional data from series of surveys	Any measure recorded in discrete time	Indicating if behaviour is changing over time	Only addresses net change. Assumes responses are instantaneous.
Lagged model with individual-specific errors	Individual-level panel data	Any measure recorded in discrete time	1. Representing influence of past history. 2. Controlling for omitted variables	Only controls for omitted variables if their effect is constant over time.
Multi-level model	Individual-level panel data	Any measure recorded in discrete time	1. Permitting behaviour to differ for sub-groups. 2. Representing variability of behaviour over time	Requires sufficient data for sub-groups.
Markov model	Individual-level panel data	Probability of transition from one state to another	Predicting patterns of behaviour over time	Describes patterns of behaviour without explaining them.
Hazard model	Continuous data	Duration in a state	Predicting time spent in carrying out certain type of behaviour	Only considers duration and not type of behaviour.
Markov renewal model	Individual-level continuous data	Probability of transition from one state to another and when this will occur	Combining capabilities of Markov model and hazard model.	Requires initial equilibrium conditions.

The proposed modelling framework for the evolutionary approach assumes decisions are made on two time frames: day-to-day and year-to-year. Levinson (1995) concentrated on the year-to-year aspect, testing an example which uses an equilibrium assumption for day-to-day decisions and lagged decisions for year-to-year change where relocation depends on congested travel times for the previous year.

The proposed model inserts into a conventional four-stage model an aggregate relocation component which estimates the number of trips between a particular origin-destination pair in the year considered as a sum of the fraction of trips from the previous year that remain and additional trips generated by switched jobs/residents and new trips due to growth. A very simple way of operationalising the model is used where 22.5% of individuals change jobs, houses or both every year (this is based on available survey data). It is acknowledged that this should be treated more realistically in future developments of the modelling approach. Levinson's model is an approach that in a simplified way addresses the churn-related issues of both life event changes and delayed responses. The underlying assumption is that relocation behaviour is boundedly rational rather than optimal since moves are lagged (for example, due to costs of moving). Land use-transport interaction models as mentioned earlier also use this approach.

Learning models

A number of researchers have proposed modelling approaches to deal with the short term (day-to-day) evolutionary processes identified by Levinson. These can be termed 'learning' models as they deal with the fact that travellers continually learn about their travel environment and adjust their behaviour. The modelling developments have been inspired by traveller information systems which have the potential to increase traveller's knowledge of network conditions. To assess the impacts of such systems it is not useful to use an equilibrium model which, as mentioned earlier, determines an 'end state' stable pattern of behaviour that is reached after an unspecified period of time.

Chatterjee *et al.* (1999) suggested the following traveller decision-making process might be applicable to learning models:

- a decision to review existing day activity-travel plan can be induced by certain events (e.g. unexpected traffic conditions);
- if there is unsatisfaction with the existing plan then a search for information on alternatives will be initiated using (i) personal knowledge (i.e. memory, experience) and (ii) other sources of information (i.e. visible traffic conditions, telematics);
- as a result of the search for information, either the plan is changed if a suitable alternative is found, the journey/activity constraints are changed, or the trip maker continues with the original plan.

Ben Akiva *et al.* (1991) have proposed a framework and statistical models for this approach to modelling. The models apply to information processing, updating historic perceptions, identifying current perceptions, transition between information levels and transition between travel patterns. Jha *et al.* (1997) specifically looked at travel time perception updating in the presence of traveller information. Travel time experience (perceived) and travel time information (perceived) are represented by random variables with a mean and variance which are updated using Bayesian techniques. Choice probabilities of route and departure time depend on the time varying travel time perceptions and are estimated using a two-level nested logit model with departure time at the higher level and route choice at the lower level. Perceptions are updated in two stages: at the pre-trip stage drivers combine historical perceptions with real-time information; travel choices are based on the updated travel time perceptions at this stage; post-trip, the perceptions before the trip are combined with the perceived experienced travel time on the current day; these perceptions become the historical perceptions for the next day.

Activity-based analysis

Activity-based analysis recognises that travel is rarely an end in itself, but rather a result of the desire of the traveller to participate in some activity at the trip destination. Activity-based models consider travel in the context of individual and household needs, goals and constraints and resulting activity schedules. In their research using activity-travel diaries to seek to better understand travel behaviour and ways of modelling it, Jones *et al.* (1983) proposed a modelling framework which includes five response domains related to activity-travel patterns.

- *Event/person* - an individual responds independently of others without affecting their activty pattern;
- *Event/inter-personal* - an individual responds affecting joint activities without affecting activty patterns;
- *Pattern/person* - an individual restructures their activity-travel pattern indepedently of others;
- *Pattern/inter-personal* - an individiaul restructures their activity-travel pattern affecting the patterns of others;
- *Environment* - an individual changes factors which are normally outside their immediate control (e.g. change job location).

Jones *et al.* (1983) developed a model for dealing with the fourth response domain of their modelling framework: - activity episode scheduling. It sees if the household can make adjustments to the timing and sequence of the set of activities they undertook before the intervention. It does this by identifying feasible permutations (using various rules) and using an objective function to select one. Other modules not developed would be used if this process fails to identify feasible options and would represent more complex processes such as changing the activity set. AMOS (Activity-Mobility Simulator, Kitamura et al., 1995) has also been designed to examine short-term responses to travel demand management measures. It takes an observed daily activity-travel pattern and determines an adaption choice using an activity scheduling model.

Other research in this area has sought to understand activity-travel behaviour better by looking in detail at participation in specific type of activities in terms of, for example, activity duration, location and time window. Bhat and Koppelman (2000) mentions that some models have addressed activity episode generation as well as scheduling and there have been recent attempts at comprehensive models which incorporate a continuous time domain.

Activity-based analysis has promise but it is the way in which it is applied that determines whether it can address the concerns of this paper. When applied to predict the change in a day's activity schedule resulting from an intervention it does not recognise longer term adaptation issues such as life event changes and delayed responses to changes. The model works in an analagous way to conventional models where it attempts to predict a new stable pattern of behaviour but for activity-travel patterns rather than single trips. On the other hand, by recognising where travel sits with respect to people's life routines it can address the over-simplification of conventional models where each traveller is assumed to make a fixed number of trips.

Activity-based analysis has the potential to reflect the routine variability of people's travel behaviour if it considers activity-travel patterns over periods longer than a day. If longitudinal data were to be used then the way in which activity-travel patterns change over time could be represented taking into account life events. Responses may also be delayed and discontinuous as well as non-reversible with respect to changes to circumstances.

Micro-simulation

Micro-simulation is an approach that can be generally applied whether it is for long run travel decisions (as discussed next) or short run travel decisions (such as day-to-day travel decisions or the activity-travel patterns discussed previously). Its explicit consideration of time (through time steps) means it is a natural way of modelling dynamics where the behaviour at time t is influenced by behaviour and experience at time t-k. It can use statistical models for traveller decision-making of any form as part of its specification.

There are examples of micro-simulation models being applied to travel demand forecasting which may offer useful approaches. MIDAS (Microanalytic Integrated Demographic Accounting System; Goulias and Kitamura, 1992) combines dynamic simulation of population with dynamic models of travel behaviour. The two main components both operate at the household level. The first component is a micro-simulator of household socio-economics and demographics which represents the progression of a household through life-cycle stages including interactions and causal paths in the lifecycle evolution of individuals and households (e.g. marriages, births, children leaving home). The output from this component is used in a dynamic model system of mobility predicting weekly levels of car ownership, trip generation, modal split, car-trip distance and transit-trip distance.

The model parameters that determine the probabilities of events occurring have been calibrated using panel data from a five year national mobility survey in the Netherlands. Sample households used in the model are also taken from the panel dataset. The sub-model components include household type transitions where logit models are used to determine transition probabilities as a function of attributes such as adult house members' age, education, employment and presence of children by age group. The income model assumes personal income at time t is determined in part by income at time t-1 (lagged dependent variable) and that there is a correlation between the unexplained effect at time t-1 and at time t (serial correlation). Many of the models in MIDAS are dynamic requiring observations from three time points in the simulation and using lagged dependent variables and serially correlated errors.

A validation exercise from one of the later waves of the panel data (that was not used in calibration) has found the model to be performing well. The model is incremented in one year time steps. Dynamic micro-simulation is advanced as a valuable tool for long term forecasting of 'what if' scenarios, although it is acknowledged that the data requirements are large and extensive

MIDAS was developed into MUVI (MIDAS –USA-Version-I) for use in a case study in the US (Chung and Goulias, 1997). US data was used to estimate the model components and a new residential relocation model added which considers people moving into and out of the area. Dynamic panel data was not available for calibrating all of the model components but was used where possible. The outputs from the demographic microsimulator were used as inputs to a transport model (of the conventional four-stage variety). For the case study in Centre County, Pennsylvania, the traffic volume predictions based on the sociodemographic estimates from MUVI (MIDAS variant) are statistically close to those based on observed census data. This indicates that the dynamic micro-simulation technique offers valuable savings in data collection in addition to its long-range forecasting capability.

Another example of a model representing life event changes is MASTER (Micro-Analytical Simulation of Transport Employment and Residences), an experimental model simulating the life decisions of individuals and households through time (Mackett, 1990). The processes undertaken by an individual in a time step (a year is used as the time step in the example described) include demographic processes (ageing, giving birth, etc.), residential moves, job moves and work, housing and transport decisions (car licence holding, car ownership, car availability, mode choice for work). The outcomes of these events are decided by using either a set of rules or by Monte Carlo simulation based on probability distributions.

Although longitudinal data is not used to calibrate models in the same way as in MIDAS, the decision made by an individual for the current time step is dependent on how their situation has changed since the previous time step. It is assumed that mode choice is only reconsidered if a significant event occurs (change of job or home, car ownership or availability, significant relative change in cost of travel by available modes). Constraints resulting from the aggregate outcome of individual decisions are taken into account by, for example, an individual remaining in their original state if no opportunities are available to change their state. The two main inputs to MASTER are a sample of individuals and households and a file of probability values.

Mackett (1990) compared for the same study area over the same time period (Leeds for 1971-91) the results from using MASTER and an aggregate-level model linking a transport model and land-use model (LILT). The results were compared with 1981 census data. Taking into account various differences in the two models the long-term elasticity values implied by MASTER tended to accord better with those found from other studies. For example, bus fare elasticities in MASTER are close to 0.3 while they are 0.6 with LILT. In MASTER the car ownership elasticity is greater for car operating costs than bus fares which is more reasonable intuitively.

Despite the promising results from these micro-simulation models it is clear that substantial research is required to examine the way in which life events influence travel behaviour and to generate models that can be used in practical transport planning applications.

7.3 Improved models

Having considered a variety of modelling approaches what can be suggested for future assessment methodology? Figure 3 is a schematic representation of travel behaviour. It illustrates the different choices that are made related to travel, representing them in rungs with each rung comprising choices that are made in a similar time frame. It acknowledges that there are dependencies and interactions between the choices that can occur on a variety of time scales. Generally a choice in one rung cascades quickly down to affect choice and travel behaviour in lower rungs whilst it more slowly affects behaviour in the higher rungs. In the example in Figure 3 the impacts on travel behaviour of planning controls are illustrated. They are expected to directly influence land use (although this is only gradual) and thereby they influence behaviour in the lower rungs (lifestyles, activities and trips). The representation has resonance with the five response domains identified by Jones *et al.* (1983).

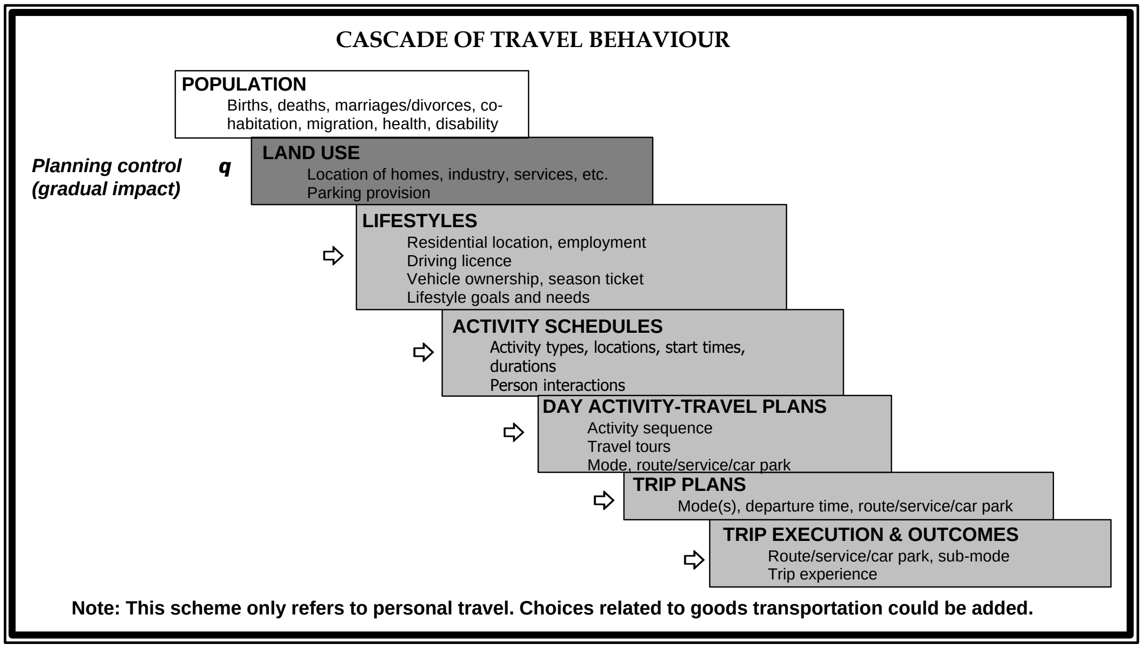

Figure 3: Cascade representation of travel behaviour

If models are to be set up that reflect this view of travel behaviour then they should encompass the philosophies discussed earlier: evolution, learning, activities. Micro-simulation provides a technique of enabling these philosophies to be implemented. The realisation of this approach to analysing travel behaviour can be achieved through developing separate models each tackling decisions made on different time horizons and able to operate independently but consistently with each other. Clearly different sorts of data need to be collected on travel behaviour than those that have been collected up to now. Panel surveys have been used successfully in the Netherlands and in the US and appear to be a priority area for the UK.

An important question is whether anything can be done in the short term to improve modelling procedures. For the short term a lack of longitudinal data is a problem. Instead of waiting for this data to become available a one-shot survey can ask retrospective questions to identify how past history influences travel choices. Recall inaccuracy is likely, however, to be too large a problem with this approach. The travel behaviour relationships currently used within models could be replaced by dynamic relationships without the need to overhaul complete model systems. A mode choice model estimated on cross-sectional data and used within a four-stage model system, for example, could be substituted by a model estimated on longitudinal data without too much disruption (most explanatory variables would remain the same). Forecasts of travel demand would then not just be made for a single unspecified future time point but for different time points in the future. Equilibrium could still be sought in terms of route choice for each of these different time points.

There may be a role in the short term for making more use of aggregate models with dynamic specifications. These can be estimated using data that is already available from past surveys. Although they cannot represent churn, they can represent delayed and non-reversible responses.

8. Conclusions

The paper has confirmed there is strong evidence for travel behaviour changing over time through asymmetric patterns of churn as opposed to transitions between stable patterns of behaviour. It has identified the causes of asymmetric churn: - life event changes; delayed and discontinuous responses; non-reversibility; routine variability. It has been argued that failing to account for each of these factors is likely to lead to unreliable models and predictions. The paper has shown that these factors are not taken into account in conventional methods but other methods can be used to account for them.

It has not been possible in the paper to prove conclusively or illustrate through data the shortcomings of cross-sectional analysis. This, however, would be a useful undertaking. Goodwin (1998) has described the use of simulation to show that failing to account for inertia in mode choice produces biased values of time. Similar investigation could be made of failure to account for other aspects of asymmetric churn. This would involve inventing a sample of individuals and simulating their behaviour over time taking into account asymmetric churn. Some individuals would leave the system and others join the system to reflect life event changes. Different models could be estimated on the data: a cross-sectional model based on the initial behaviour of the cross-section of individuals; a lagged model which ignores new entrants and departees; and a model specified to take into account new entrants and departees.

A new modelling approach is required that recognises dynamics. This call has been made before, for example, with respect to traffic management and information systems. It is now made with respect to all types of intervention. Research needs to be undertaken to assess the improvements in forecasting capabilities of models with dynamic specifications and models dealing separately with the different components of change (e.g. ‘reducers’ and ‘increasers’). Short term progress will be possible through the incremental replacement of cross-sectional data based models with longitudinal data based models where they become available. Long term progress requires establishment of modelling systems that recognise behavioural adaptation is a continual process.

It is the underlying movements in behaviour that cause a break in overall trends and need to be understood. Looking at overall change or independent samples at two points of time does not allow the underlying movements to be examined and understood. We are interested in travel behaviour changes at the marginal level and not the average level (i.e. the details of those changing their travel behaviour). We need to understand marginal changes to understand the process of change and be able to influence it effectively. Asymmetric churn is a concept requiring serious and urgent consideration by the transport planning community. As a start, a clear explanation of what the concept means would no doubt help this to be achieved and it is hoped that, if nothing else, the paper helps in this way.

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This paper has arisen from the Transport Planning Society's 2000/2001 Bursary Award Scheme. The Scheme is designed to encourage thinking by younger professionals in transport planning and to address current topics of relevance. For further details visit www.tps.org.uk