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A Comparison of Sample Enumeration and Stochastic Microsimulation for Application of Tour-Based and Activity-Based Travel Demand Models

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Abstract

The paper compares two travel demand forecasting approaches that have been applied to forecast travel demand in and around Portland, Oregon. Both approaches apply a system of discrete choice models to a synthetic sample of households, drawn to match the characteristics of the actual or forecast population. The system consists of a model to predict a full day's schedule of tours (by purpose and trip chain type), a model to predict the times of day at which each tour begins and ends, and a model to predict the locations of all out of home activities and the modes used to reach them. The accessibility of travel by all modes and locations also appears in the upper level models to influence the number of tours and stops made at various times of day.

Rather than focusing on the models themselves, the paper contrasts two methods of applying them. In sample enumeration, the probabilities across all possible alternatives are added across all individuals in the sample. The output consists of origin/destination tour and trip matrices, segmented by purpose, mode, time of day and income class. In stochastic simulation, the probabilities are used in a Monte Carlo fashion to predict a single set of tours, destinations and modes for each individual in the sample. Thus, all household and person characteristics can be tied back to each individual trip record so that the output resembles a "synthetic travel diary survey".

The paper provides various comparisons of using the two approaches. A major advantage of the microsimulation method is that much more detail can be retained in the output. The simulated trip records can be aggregated in a flexible way to create trip matrices, perform equity analyses, or input to dynamic traffic simulations. The microsimulation framework also provides more flexibility in applying specific sub-models. For example, models for work-based tours and intermediate stop locations had to be applied in an aggregate manner in the sample enumeration, but could be applied disaggregately with much less processing time in the microsimulation. Disadvantages of the microsimulation approach can include less spatial coverage across possible OD pairs, and less stability in results due to the use of random draws. Both of these disadvantages, however, can be counteracted by using much larger synthetic samples. In Portland it is possible to simulate the entire Portland population (1.5 million person records) with the microsimulation approach in less run time than is required to run just one tenth as many records in the sample enumeration.

1. Introduction

The trip-based 4-step approach that is typically used to predict travel demand in urban areas is not a very accurate representation of how people actually make travel decisions. A great deal of research has been done into trip chaining and activity patterns as key determinants of travel behavior. Over the last ten years, these concepts have begun to make their way into the models used by urban and regional planning organizations, but the progress has been much slower than one might hope. One reason for this has been the difficulty of applying such models in practical settings.

In this paper, we compare two approaches that can be used to apply tour-based and activity-based travel demand model systems: sample enumeration and stochastic simulation. In sample enumeration, the probabilities across all possible alternatives are added across all individuals in the sample. The output consists of origin/destination tour and trip matrices, segmented by purpose, mode, time of day and income class. In stochastic microsimulation, the probabilities are used in a Monte Carlo fashion to predict a single set of tours, destinations and modes for each individual in the sample. Thus, all household and person characteristics can be tied back to each individual trip record so that the output resembles a "synthetic travel diary survey".

In section 2, we present some background on the development and complexities of tour-based and activity-based travel demand models for practical forecasting. In section 3, we describe and contrast different approaches for applying these various types of models. In section 4, we summarize our experiences from recent projects in Portland, Oregon. In section 5, we described plans for further development, and discuss important areas for further research.

2. Tour-based and activity-based forecasting models

2.1. Conceptual background

Since the development of the UTPS model framework in the 1960's, most travel demand forecasting has been done with various modifications of the trip-based 4-step approach: trip generation, trip distribution, mode choice and assignment of origin-destination matrices to highway and transit networks. While the route choice assignment process may make sense in the context of a single trip, travel decisions about how often and when to leave home, where to go to, and which mode of travel to use are clearly made for more than one trip at a time. At the very least, the mode, destination and departure time for a trip leaving home will be key determinants of the trip back home. If multiple stops are made along the way before returning home, a whole chain of trips will be influenced by the same travel decisions.

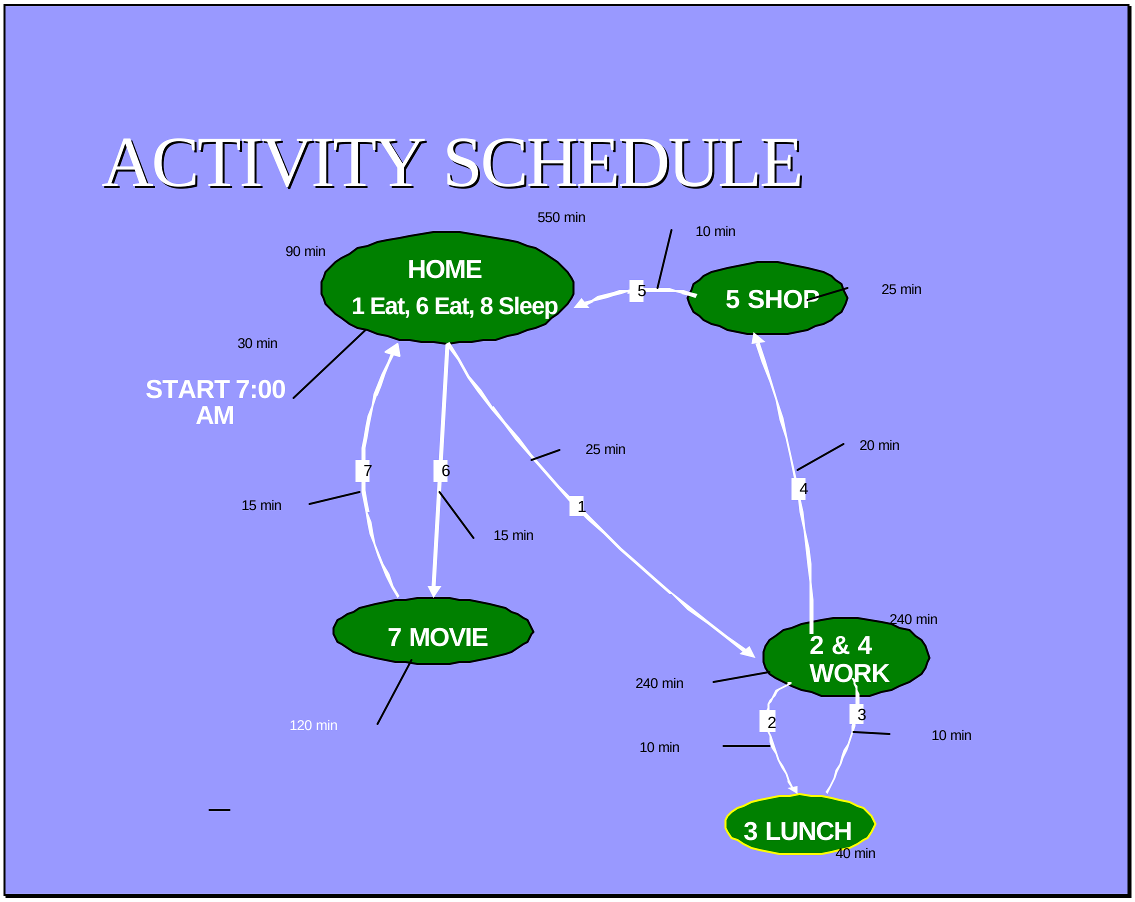


Figure 1 / Table 1

Approach	Modeled decision units	Trips
Trip-based	1 home-based work (HBW) trip 3 non-home-based work (NHBW) trips 3 home-based other (HBO) trips	1 2,3,4 5,6,7
Tour-based	1 home-based work tour, with a stop on the way home 1 work-based tour, with no extra stops 1 home-based other tour, with no extra stops	1,4,5 2,3 6,7
Day-pattern	A primary work tour, with a work-based subtour, a stop on the way home, and a secondary non-work tour	1,2,3,4,5,6,7

The distinction is depicted in Figure 1 and Table 1. With the trip-based approach, the representative trip diary day would be broken down into 7 independent trips, 3 of which are non-home-based. Non-home-based trips are often poorly modeled using trip-based approaches. In effect they become "orphans", because it is difficult to tie them back to specific residence zones and types of households. In the tour-based approach, there are 3 tours, two of which are home-based and a third that is work-based. Two of the tours are simple out and back, while the home-to-work tour includes an extra stop for shopping on the way home.

Although the tour-based approach captures more of the behavioral interactions across trips, it can still miss some important ones. For example, the mode of travel and departure times for the work-based subtour will tend to be constrained by the mode of travel and departure times for the home-based work tour that "surrounds" it. Also, if the person makes a stop for shopping on the way home from work, it becomes less likely that that person will stop for shopping as part of the other tours – on the way between work and lunch or between home and the movie. Thus, changes to one tour can also influence the aspects of other tours made during the day. In Table 1, a third approach is named the "day-pattern" approach because it treats all of the trips made during the day as parts of the same decision process. We can more generally refer to this as an "activity-based" approach because it can deal simultaneously with the participation in various types of activities (including in-home activities) across the day, and with the apportioning of those activities into home-based trip chains, i.e. tours.

The more technical aspects of these approaches will become more apparent in later sections. First, some historical background may be useful.

2.2. Historical background

Some of the first practical applications of tour-based modeling for forecasting were created by Hague Consulting Group for various regions in the Netherlands in the early 1980's (Gunn, et al. 1986), resulting in the Dutch National Traffic Model (Gunn, et al. 1987). In the early 1990's, tour-based models were also implemented in Stockholm (Algers et al. 1995). The Swedish model system uses an advanced model structure which also includes some interactions between the work tour patterns of different household members. There have been more recent implementations of tour-based models in other European countries (e.g. Cascetta and Biggiero 1997).

In the United States, tour-based modeling has only been implemented in the last 5 years or so – by Cambridge Systematics in Idaho and New Hampshire (Rossi and Shiftan 1997), and in current projects by Parsons Brinckerhoff in Honolulu and New York City. These model systems have included explicit models to predict the locations of any intermediate stops along the tours – an aspect that was missing from some of the earlier European models that were designed to predict use of the major national or regional transport networks only.

Activity-based modeling approaches have been the subject of a great deal of research. Some of this research stays within the nested discrete choice modeling paradigm (Ben-Akiva and Lerman 1985) used for the tour-based models above (e.g. Bowman and Ben-Akiva 1999; Wen and Koppelman 1999), while others have advocated bringing in additional types of models such as activity duration models (Bhat 1999), neural network models of transition (Pendyala et al. 1997), and constrained optimization methods (McNally 1998).

Over the last few years, we have had the opportunity to develop the day-pattern activity-based modeling approach introduced by Bowman and Ben-Akiva (1998) for implementation at Portland METRO, the metropolitan planning organization for the region around Portland, Oregon. The first work was done as a project for the Travel Model Improvement Program (TMIP) for the US Department of Transportation (Bradley, et al. 1998). The resulting model system was first applied as part of a congestion pricing assessment project for Portland, and is now being updated for use in further projects. Part of this update has included the switch from a sample enumeration framework to a stochastic microsimulation framework for application, and this will be discussed in later sections. The authors, along with Cambridge Systematics and Parsons Brinckerhoff, are also involved in developing and applying a similar activity-based microsimulation forecasting model for the San Francisco County Transportation Authority.

2.3. Advantages and complexities of the tour-based and day-pattern approaches

Before moving on to implementation methods, it is worthwhile to point out some of the practical difficulties with these newer modeling approaches. As stated above, the major advantage of both approaches is that they capture interactions between different trips and between different tours and activities made during the same day. A policy that affects one trip or tour can have repercussions on other trips or tours, in terms of the modes used, the locations, the timing, and even whether certain activities are carried out at all. One might hope to avoid this complexity by assuming that these “knock-on” effects will cancel out when taken across all travelers in a given area, but there is no reason to expect that to be the case. That would just potentially add aggregation error on top of the “disaggregation error” that comes from treating trips as wholly independent events.

Tour-based approaches require disaggregate model estimation at the level of the individual, and this can already present a practical difficulty to less experienced modelers. Also, processing trip-diary data to form tours and day-patterns from the data can be a tricky and time-consuming process. There do not yet exist widely-used conventions or software for doing this. Also, the structures of the models tend to be more complicated than typical trip-based models, and this can also cause some difficulties in estimation, particularly if one wants to use nested models with logsum linkages.

These types of models tend not to “fit” into the more widely used packages that are used to prepare network data for travel demand models and then to apply the resulting models (EMME/2, MINUTP, TRIPS, etc.). The decision making “unit” is not a pair of zones, but a person-day or a trip-chain, and a single trip chain can have stops at several different zones. As a result, it is necessary to create custom software to apply most tour-based or activity-based models. This can be a practical obstacle, but it also opens up opportunities to decide which method of application is most efficient and useful. That is the subject of the following sections.

3. Sample enumeration and stochastic simulation

3.1. Conceptual background

The most typical form of model application to date has been zonal enumeration. For each travel zone, the number of trips by each mode to each destination zone at each time of day is calculated. This may be the product of the outputs of different models – e.g. the number of trips generated, times the fraction to each destination, times the fraction by each mode. Model probabilities are used to distribute demand across all feasible alternatives.

Sample enumeration follows an analogous approach of multiplying conditional probabilities. In this case, however, instead of applying the models separately for each travel zone, we apply them for each household and/or person in a representative sample. Thus, sample enumeration tends to work on a less aggregate scale than zonal enumeration, but that is not necessarily the case. Zonal enumeration can work with many different segments of the population in each zone, so that we are essentially working with an expanded sample of representative household/person types. Sample enumeration can work with large samples, or else with smaller samples with expansion factors to weigh up to the total population. At some intermediate stage, the two approaches can come to resemble each other. The usual defining difference, however, is that sample enumeration retains more complete information about each person and household in the sample – not just those characteristics that are used to define market segments. As a result, sample enumeration allows a wider range of variables to be included in the models that are applied. In addition, if models are estimated disaggregately at the level of the person or household, then sample enumeration applies them at the same level, avoiding possible aggregation bias.

In stochastic microsimulation, the key difference is that instead of enumerating all possible combinations of model outcomes and multiplying probabilities, a single outcome is predicted from each model, drawing randomly from the model probabilities using a stochastic Monte Carlo approach. This introduces some random sampling error into the forecasts, which decreases as the number of households simulated increases. Conceptually, each random draw can be thought of as the choice made by a single person or household, given the odds predicted by the model. For both of these reasons, this approach typically uses large samples with little or no expansion – i.e. simulating (nearly) as many different persons as are actually in the population.

Table 2 indicates which type of application is typically used with which modeling approach. Trip-based models are typically applied using zonal enumeration, so that all steps of the model system can be implemented within a matrix-based network package. Even if such models have been estimated using disaggregate data, they are often applied at the aggregate zonal level. There is no reason why trip-based models could not be applied using sample enumeration or stochastic simulation, but it has not been done often in practice.

Table 2: Application approaches for each modeling approach

Approaches	Zonal enumeration	Sample enumeration	Stochastic simulation
Trip-based	TYPICAL	Possible	Possible
Tour-based	Possible	TYPICAL	Possible
Activity-based	Possible	Possible	“TYPICAL”

Tour-based models have generally been estimated at the disaggregate level, and so they have often been applied that way using sample enumeration. Sometimes a combination of application approaches has been used: for example using sample enumeration for the more demographic-sensitive models like tour generation, and switching to zonal enumeration for the more network/land use-sensitive models like tour destination and mode choice. The combination to use in each case involves a trade-off between considerations like computer run-time and the geographic coverage and accuracy of results.

There is no typical application method yet for activity-based models, since so few have been used in practice. From the work now in progress, it appears that stochastic simulation may be the most common approach. In the Portland day-pattern models described in the following section we have used all three approaches to some extent.

Note that all of these combinations of modeling approaches and application approaches can eventually produce the same type of output: O/D trip matrices by mode, time of day, and purpose that can be put into highway and transit assignment packages to predict network flows and travel times. The travel times can then be iterated back to the forecasting models to ensure consistency. Any of the approaches could also be used with traffic network microsimulation instead of equilibrium assignment. Although that is not the type of simulation we are discussing here, the greater level of output detail possible with stochastic simulation of travel demand that may make it more compatible with simulation of traffic systems. (More on that later.)

3.2 Advantages and complexities of sample enumeration and stochastic simulation

The primary advantage of both approaches is that they allow the demand models to be applied to individual travelers, incorporating the wide diversity of behavior is that is observed in travel diary data, and thus avoiding aggregation biases.

A disadvantage is that neither of these approaches are included within “off the shelf” network modeling software, so custom software will need to be written. As mentioned previously, this situation is already the case for tour-based and activity-based model structures in general, so it will not be an additional obstacle for those types of models. As these approaches are used more in practice, we can hope that they will be incorporated into the existing application software packages, or that new packages will come on the market.

In general, the more complex the model structure and the more levels there are in the "decision tree", the more costly it becomes to calculate and store in memory the probabilities for all of the combinations of probabilities that are required for sample enumeration. Stochastic simulation gets around this problem by "paring the tree" down to a single branch at each level, and then continuing down the tree from there.

An additional advantage of the microsimulation approach is that it simulates a single single set of tours, destinations, modes and departure times for each individual in the sample. Thus, all household and person characteristics can be tied back to each individual trip record so that the output resembles a "synthetic" travel diary survey. This type of output provides a wealth of information, not only for assignment to networks, but also for calculating evaluation and equity measures. Output in the form of individual trips starting at specific times is also very convenient for input to dynamic traffic network microsimulators.

There are other, more subtle, differences between sample enumeration and stochastic simulation that are best discussed in terms of specific examples. In the next section, we describe specific applications developed for the Portland metropolitan area.

4. Recent experience in Portland

4.1. The sample enumeration application

As mentioned in Section 2, the activity-based models created for Portland METRO are based on the day-pattern approach developed by Bowman and Ben-Akiva (1999). The models were estimated using data from a two-day household travel and activity diary survey carried out in 1994, combined with land use and road and transit network data for 1244 zones in the metropolitan area.

The models estimated from the data included:

- Household car ownership.
- The pattern of tours for the day for each person in the household. This is a combination of:
    - the primary activity type (work/school, maintenance, discretionary; in home, out of home),
    - the number of intermediate stops on the way to and from the primary activity,
    - whether or not any work-based subtours are made,
    - the number and purpose of secondary home-based tours.
- The time period of the day leaving home and returning home for each tour.
- The primary destination and mode used for each tour.
- The locations of any intermediate stops made on each tour.

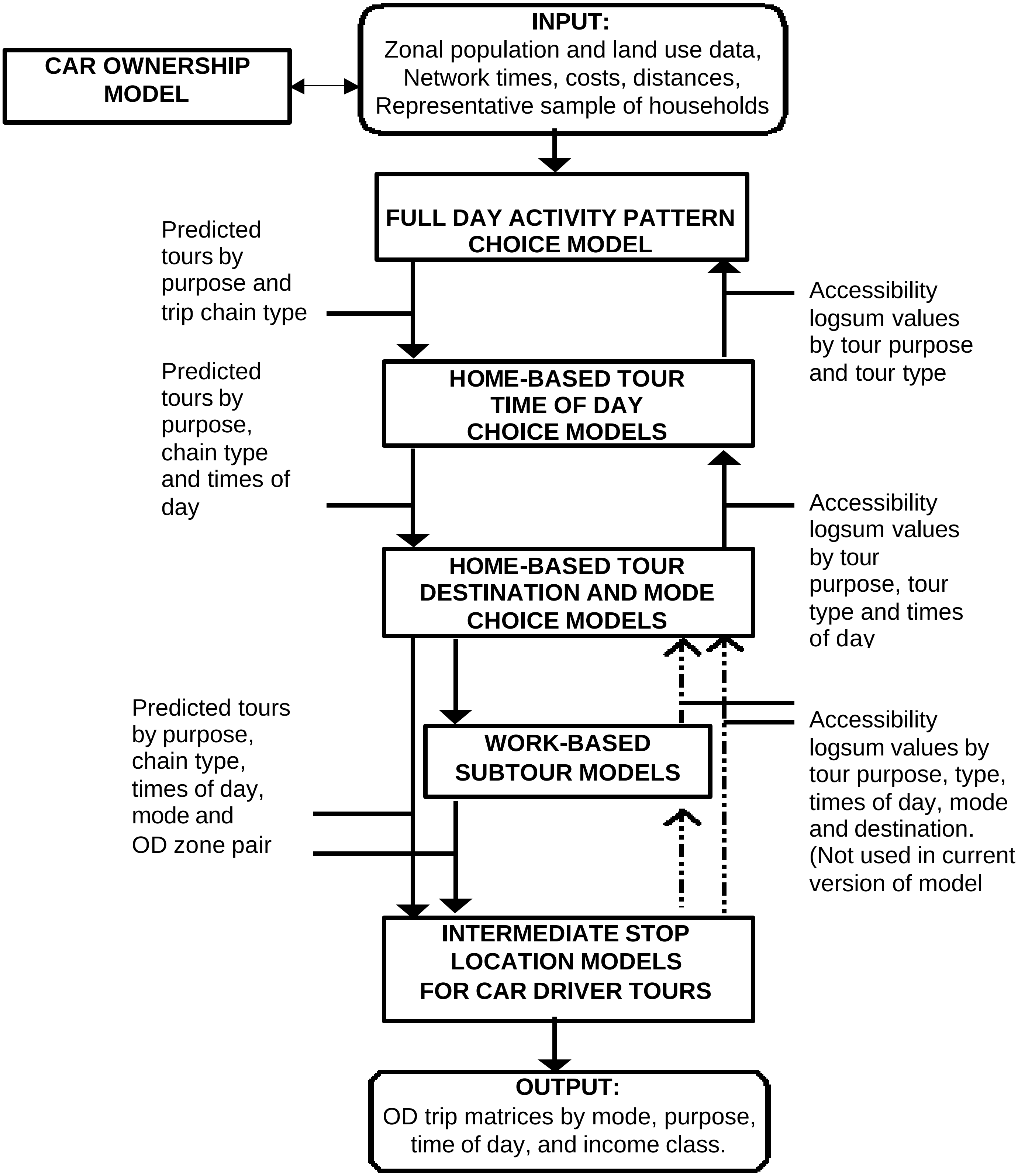
Details of these models and the sample enumeration application framework are given in Bradley et al. (1998) and Bowman et al. (1998). A simplified diagram is given in Figure 2. The first two types of input data are common to most model applications: zonal population, employment and land use data, and zone-to-zone car and transit level of service data for different times of day (AM peak, midday, PM peak, and off-peak). The third type of input is less common: a "synthetic", or "prototypical" sample of households and individuals for the region. This was created using the US Census 1990 PUMS 5% micro-data sample for the region, and then drawing the appropriate households to match the actual or forecast population distribution within each zone. This procedure is described in Beckman et al. (1995). For each zone, we drew the appropriate number of households within 64 different segments; all combinations of 4 household size categories, 4 age of head of household categories and 4 household income categories. The land use model used at Portland Metro predicts the population distribution across these 64 categories in each zone for forecast years. Our sample for the base year (1994) contains about 0.6 million households and 1.5 million inhabitants, matching the actual population in that year.

The model system depicted in Figure 2 shows arrows going down the left-hand side, representing the conditional model probabilities that are carried down the decision tree. By the time we reach the bottom of the tree, we have a huge combination of probabilities for all combinations of tour types, tour origins and destinations, times of day, and modes of travel. The arrows going up the right-hand side represent logsum, or expected utility values that enter the higher level models from the lower ones. For example, the accessibility of travel by all modes to all destinations at various times of day influences the time periods during which the tour is made. In turn, the overall expected utility of making various types of trip chains across the day will influence the activity pattern of the individual in terms of the number and purpose of out of home activities undertaken and how those activities are arranged into tours.

Using logsums in this way means that we first need to calculate the utilities of every combination of alternatives going "up the tree" before calculating probabilities on the way back down. This makes the procedure very computation intensive. To reduce computer run time to an acceptable level, we introduced three main types of short cuts:

- We ran most simulations with a partial sample of households – e.g. applying the models to 1 out of every 10 households while giving each household an expansion factor of 10.
- The destination choice and stop location models were applied to only a subsample of the 1244 possible zones. We typically used 20 zones as choice alternatives, selected randomly using stratified sampling based on distance and employment levels. This sampling is done "on the fly" for each person during model application.
- Instead of applying the work-based subtour and intermediate stop location models at the level of the individual, we accumulated them at the zone-to-zone level, and then applied these lowest-level models at a more aggregate level using zonal enumeration. This means that we could not use the logsums from these lowest level models in the higher models, as indicated by the dashed lines in Figure 2. In simpler language, this system uses sample enumeration at the individual level to generate zone-to-zone home-based tour matrices, and then uses zonal enumeration to split those tour matrices into trip matrices for assignment.

Figure 2: The Portland Day-Pattern Model System: Sample Enumeration



Running on about 60,000 households (a 1 in 10 sample), this model system takes about 32 hours to run on a 400 Mhz Pentium II computer. Only about 25% of that time is needed to run the sample enumeration part of the system, while over 75% is needed to run the zonal enumeration to calculate the distribution of intermediate stop locations between every OD pair in the region. This indicates that the need for splitting tours into trips by accounting for intermediate stops is a major obstacle for using the sample enumeration and zonal enumeration frameworks.

4.2. The stochastic microsimulation application

As part of further research, we applied the same set of discrete choice models, this time using a stochastic simulation approach. The structure is depicted in Figure 3. Again, we use the models and logsum linkages to calculate utilities "up the tree" for each individual, from mode and destination choice, through time of day choice, up to the full day activity pattern choice. This time, however, instead of calculating probabilities for all combinations of alternative down the tree, we use the following procedure:

- Use the Monte Carlo approach to draw a single full day tour pattern from the model probabilities.
- If the primary activity of the day is performed out of home, draw the times of day for the primary tour stochasticly from the tour time of day model probabilities.
- Use these predictions to sample a corresponding day-long sequence of observed activities from the household survey data.
- For each tour in the pattern, including work-based subtours, sample from the destination and mode choice model probabilities to replace the observed destination and mode in the activity list.
- For any intermediate stops in any tours, apply the intermediate stop location models stochasticly to assign locations to those activities.

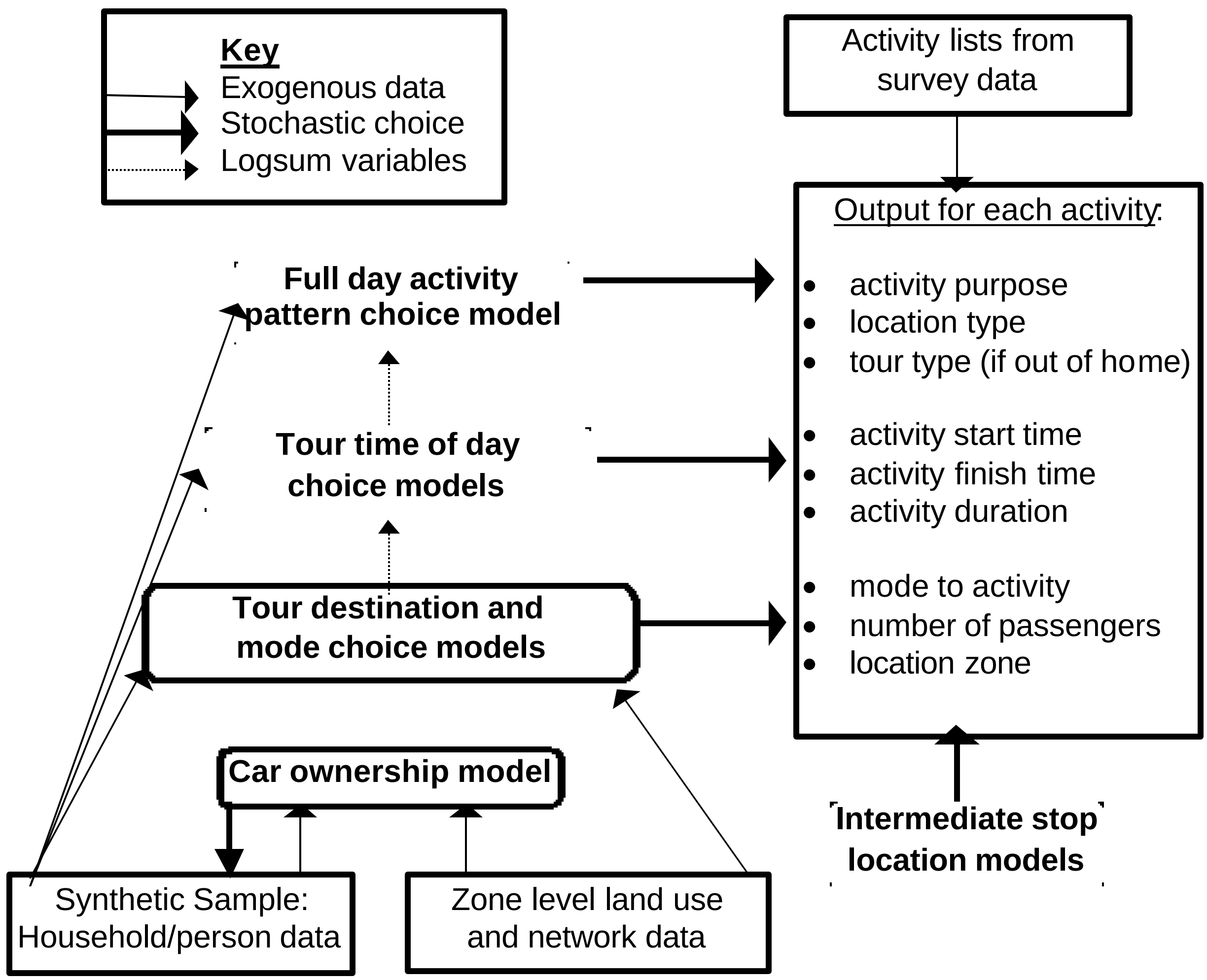
The output for each individual in the sample is a list of activites, including the accompanying information for each activity shown in Figure 3. Note that, although we are drawing lists of activities from the survey data, almost all of the survey data information is replaced by choice data synthesized from the models. The only details retained from the survey activity records are the more precise timing and sequencing of activities, since our time of day models only deal with five different time periods.

Using this approach, we were able to avoid making some of the shortcuts that were necessary with the sample enumeration approach:

- We could run the model system on the full sample of 600,000 households in 30 hours on a Pentium II 400 – less time than was needed to run the sample enumeration/zonal enumeration system on only 60,000 households.
- We still needed to use a subsample of destinations in the location choice models, but since the models are now only simulating a single choice made by a single individual, it seems more acceptable not to include all zones in the choice set.

- The work-based tour models and intermediate stop locations models are now applied at the individual level instead of the zonal level. In the microsimulation, these models only need to be applied when such stops are actually predicted, saving a lot on run time. However, we still did not include the logsums from these models in the upper level models. That is still a topic of continuing research (see Section 5).

Figure 3: The Portland Day-Pattern Model System: Stochastic Simulation



We had two primary concerns with using stochastic simulation for practical forecasting. First, how much random sampling error would be introduced into the forecasts? Second, would simulating a single set of choices per individual lead to a lack of geographic coverage, i.e. a lot of "holes" in the resulting trip matrices? When simulating every individual in the population separately, these issues do not appear to be problems. Along major overall indicators, the results from different microsimulations using different random number sequences did not differ by more than 1 or 2 percent from each other or from the sample enumeration results. When looking at more focused results, however, such as the number of trips made by a certain income group between one set of zones and another set of zones, the percentage differences can be much larger. In other words, the absolute differences between the forecasts will tend to be small, but the percentage differences can be large if they are based on values that are very small to begin with.

Two additional notes about random sampling error: Any model application system that uses sampling of alternatives such as in destination choice models already contains some random sampling error. Also, stochastic sampling error is likely to be small compared to the many sources of error already present in the models (measurement error, specification error, input forecast error, etc.), so one could view random sampling error as a small reminder that the forecasts are only approximate estimates anyway, and that very small differences between forecasts should not be given too much importance.

5. Discussion of further research

We are currently undertaking research to further improve and expand upon the models and microsimulation framework described above. Some of the important areas for near-term development include:

- Including logsums from the intermediate stop models in the tour primary destination and mode choice models, to represent the fact that being able to chain together activities is an attractive feature of a mode or location.

- Using network links as locations rather than zones – in effect giving us about 20,000 zones instead of 1244. (Since the microsimulation approach loops on individuals rather than zones, this will not influence run time, but it will increase data storage requirements.)

- Instead of drawing observed sequences of activities from the household survey data, using simple models based on observed distributions to fully synthesize all of the details in the simulated activity patterns.

- Including an extra set of mode choice and departure time models at the bottom levels of the system, to make phenomena such as mixed-mode tours and departure time shifts within time periods (peak-spreading) endogenous to the system.

- Extending the system to predict travel for children. (Currently the models are estimated and applied only for those age 16 and over.)

- Modeling workplace location and (possibly) school location at the top level of the system. Choices such as auto ownership and activity-pattern choice would then be conditional on commute distances and land use around the work location.

- Explicitly modeling joint activity participation and travel among household members. This will include both joint tour-making and picking up and dropping off passengers.

Shifting from a person-based model to a household-based model will certainly be the most challenging part of the current development program. Since the current person-based models already include many variables related to household type and composition, it is not clear whether making these interactions explicit will have much influence on the forecasts, but it certainly seems worth the effort to find out.

Another ongoing area of work is the calibration/validation of the microsimulation system to external data sources. In most respects, this effort is similar to the calibration of trip-based model systems. One area where it may differ is in the adjusting of overall trip rates. Usually, trip generation models based on household survey data need to be adjusted upwards due to non-response and non-reporting bias. We hypothesize that these biases may be quite different for different types of activity patterns. For example, those people that that do not perform any activities during the day and those that perform very many activities may be least likely to respond to the survey, for differing reasons. The day-pattern model structure will allow us to recalibrate to reflect these differences, although there is very little hard evidence with which to do so.

Another area is the balancing of predicted work trips to the zonal employment data and forecasts. Using the simulation approach, we can keep track of how many people are predicted to work in each zone, and then make that zone unavailable for the rest of the simulated individuals. This seems more attractive than the typical k-factor approach, but some work will be needed to see how well it works in practice.

As part of the current development work, we also plan to implement this model system to generate activity patterns for the test implementation of the TRANSIMS microsimulator in Portland during the year 2000 (Texas Transportation Institute 1999).

An interesting area for longer term development would be to expand the scope of the simulation to look at how behavior changes over time. One way to do this would be to use panel data to introduce some state-dependent dynamics into the activity pattern models. For example, given a person's observed activity pattern a year earlier and any changes that have taken place recently, what activity pattern will that person choose this year? The day-pattern approach described here could be extended in that direction given decent longitudinal data and advanced estimation techniques. It would also require a microsimulation framework that ages households over time, simulating births, deaths, marriages, divorces, etc. Ideally, the system would also simulate households and employers changing locations within the region and moving into or out of the region. In that regard, linkage with a land use microsimulation model such as UrbanSIM (Waddell 1998) would be an exciting possibility.

In light of the wide variety of activity-based travel research in recent years, some might argue that it would be better to move away from the utility-maximizing discrete choice framework altogether. There may be some merit to such arguments, but we also should not underestimate the value of the years of practical experience built up using discrete choice models for urban and regional forecasting. Our approach has been to try to improve and expand upon the techniques in place, in the hopes of pulling the state of the practice forward.

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