DEMONSTRATION OF AN ACTIVITY-BASED MODEL FOR PORTLAND

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Abstract

We report the first operational implementation of an activity-based travel demand model system proposed in 1994 by Ben-Akiva, Bowman and Gopinath. Integrated disaggregate discrete choice models represent an individual's demand for activity and travel as an activity pattern and a set of tours. The system explicitly represents total daily demand, trip chaining, inter-tour and at-home vs on-tour trade-offs, as well as timing, mode and destination choices. Preliminary application results demonstrate the model's ability to capture activity substitution, time of day shifts and increased leisure travel demand in response to a congestion pricing policy.

INTRODUCTION

We report the first operational implementation of an activity-based travel demand model system proposed in 1994 by Ben-Akiva, *et al* (1996) and subsequently demonstrated as a prototype for the Boston metropolitan area (Bowman, 1995; Ben-Akiva and Bowman, 1997). The development of the model, called the activity schedule model, can be viewed as the third step in the evolution of disaggregate econometric model systems toward an activity basis. In the first step, integrated disaggregate trip-based choice models used linkages across models, providing a partial representation of time and space constraints and household interactions. The MTC system (Ben-Akiva, *et al*, 1978; Ruiter and Ben-Akiva, 1978) was developed for the San Francisco Bay Area, and has been used in forecasting for many years. A second step took place with the introduction of tour-based models in the Netherlands (Daly, *et al*, 1983; Gunn, *et al*, 1987). Tour-based models capture the effect of trip chaining by using the tour as the basic decision unit, that is, all the activities and travel occurring between the departure from home and subsequent return. Recent tour-based model systems have been developed for Stockholm (Algers, *et al*, 1995), Salerno, Italy (Cascetta, *et al*, 1993) the Italian Transportation System (Cascetta and Biggiero, 1997), Boise, Idaho (Shiftan, 1995) and New-Hampshire (Rossi and Shiftan, 1997). Now, the third evolutionary step introduces more model integration, representing an individual's choice of activities and travel for an entire day (activity schedule, or schedule for short). It extends aspects of trip and tour-based models, and can be integrated with other existing components of forecasting model systems, including land use, mobility and transport supply models. The system can be estimated, tested and validated using accepted statistical procedures.

Demand for activity and travel is viewed as a choice among all possible combinations of activity and travel in the course of a day. As shown in Figure 1, the schedule consists of a set of tours tied together by an overarching activity pattern (pattern). The pattern extends the linkage beyond that of a tour-based model to include all the tours that occur in a single day and at-home activities, thereby explicitly representing total daily demand and the ability of individuals to make inter-tour and at-home vs on-tour trade-offs. For example, the model can capture the choice between combining activities into a single tour and spreading them among multiple tours, incorporating the factors that influence this type of decision. Many situations of interest, such as demand management programs, ITS deployment and increased fuel prices, can induce these kinds of activity, and travel schedule responses.

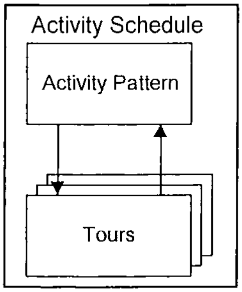

Figure 1: The Activity Schedule Model Framework. An individual's multidimensional choice of a day's activities and travel consists of tours interrelated in an activity pattern.

In the model, tour decisions are conditioned, or constrained, by the choice of activity pattern. This is based on the notion that some decisions about the basic agenda and pattern of the day's activities take precedence over details of the travel decisions. The probability of a particular activity schedule is therefore expressed in the model as the product of a marginal pattern probability and a conditional tours probability,

$$p(schedule) = p(pattern)p(tours \mid pattern) , \quad (1)$$

where the pattern probability is the probability of a particular activity pattern and the conditional tours probability is the probability of a particular set of tours, given the choice of pattern.

The choice of pattern is not independent of the conditional tours decisions. Rather, the relative attractiveness—or utility—of a pattern, depends on the expected value of the maximum utility to be gained from its associated tours. Through this expected utility, the pattern's choice probability is a function of the attributes of all its available tours alternatives. This relation captures sensitivity of pattern choice—including inter-tour and at-home vs on-tour trade-offs already mentioned—to spatial characteristics and transportation system level of service, and is a very important feature of the model system.

THE STRUCTURE OF THE ACTIVITY-BASED MODEL SYSTEM

An ideal activity-based model system includes full information on the chain of activities each person in the household is involved in throughout the day. This information includes time of day, duration, activity type, location, travel mode, and travel time for each activity. The model structure is designed get as close as possible to such an ideal model system, considering the need to implement it immediately by Metro, the Portland, Oregon, metropolitan planning organization. Although compromises were made, the main features of the activity-based model were retained. The remainder of this section describes the model system as implemented.

Tour Concepts

Figure 2 illustrates the tour concepts that are important in understanding the model structure. A tour is defined as a sequence of trip segments that start and end at home. Each tour can have a number of stops, classified by three purposes: subsistence (work or school), maintenance, and discretionary. Each tour has a primary destination. Work is the primary destination for tours with a work stop exceeding a threshold duration. For other tours a set of rules based on a combination of purpose and duration of activities determine the primary destination.

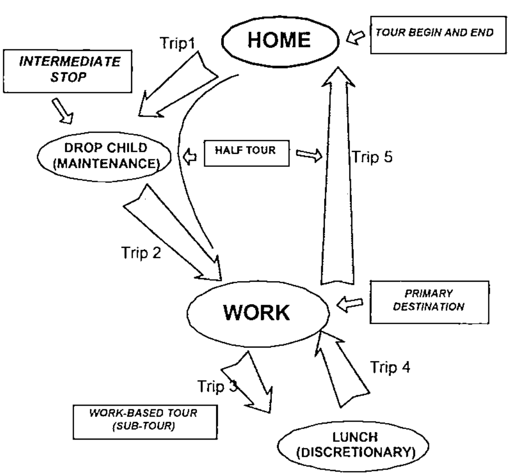

Figure 2: Tour Concepts

The portion of the tour from home to the primary destination is called a half tour, and the portion of the tour from the primary destination to home is the other half of the tour. All stops other than the primary destination are called intermediate stops. One or more activities may take place at each stop location, so the duration of a stop can be quite long, although it is usually less than the time spent at the primary destination. Subsistence tours may have a work-based (or school-based) subtour. A work-based tour is defined as a sequence of trip segments that start at work and end at work. For example, a person leaving work for lunch and coming back to the office is making a work-based subtour.

The Overall Model Structure

Figure 3 shows the overall structure of the activity-based model system. It is a system of disaggregate logit and nested logit models assuming a hierarchy of the model components, with five types of models in the hierarchy. Lower level choices are conditional on decisions at the higher level, and higher level decisions are informed from the lower level through expected utility (accessibility) variables.

The models are disaggregate in that they include demographic and socioeconomic descriptor variables that can vary for each household and person in the sample. Residence area land use is also included in the models at the traffic zone (TAZ) level. Destination land use variables and network times and costs for car and transit are used in the Mode and Destination models and the Intermediate Stop Location models. These variables are not used directly in the Times of Day or Activity Pattern models, but their influence is captured through the "accessibility logsum" variables, which represent the expected utility across all possible modes and destinations in the lower level models.

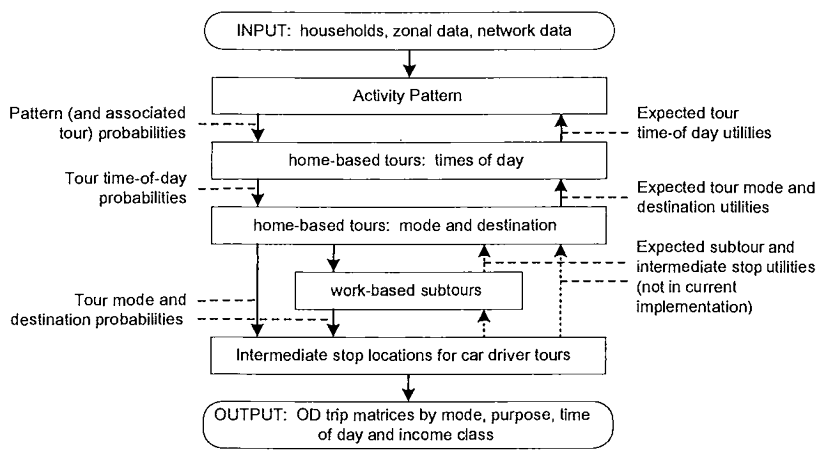

Figure 3: Portland Activity Schedule Model System

The models for Work-Based Subtours and Intermediate Stop Locations use aggregate categorical variables (income and home-based tour mode and times of day), and none of the higher level models use accessibility logsums from these two lowest levels. This departure from the system design was made so these two types of models could be applied at a more aggregate level, making it feasible to apply the entire model system using current Pentium-based microcomputers.

The Household Activity and Travel Survey Data

In 1994, a household survey was carried out in Portland and surrounding counties. Data was collected about the household and its members, and each member of the household completed a two day diary listing all on-tour activities, major at-home activities, plus all travel. The survey contained roughly 5,000 households, giving more than 10,000 persons and 20,000 person-days of travel and activities. All activities were geocoded with over a 95% success rate for addresses within the current Metro study area. We subsequently refer to these data as the RP data.

A number of stated preference (SP) experiments were also carried out in conjunction with the household survey. For this study, the most relevant experiment was one that looked at mode choice, time of day choice, route choice and travel frequency in response to changes in travel times, fuel costs, transit fares, and, most importantly, hypothetical tolls introduced on major roads.

In order to use the survey data in model estimation, it was necessary to (a) merge corresponding household, person, activity, and location data, (b) classify the activity and travel sequences into tours and activity patterns, (c) draw samples of alternative destinations for the mode and destination choice models and intermediate stop location models, (d) attach zonal land use data to tour origins and alternative destinations/stop locations, and (e) attach zone-to-zone car and transit times, costs and distances to all possible tour origin/destination pairs

The Activity Pattern Model

The highest level of the model system is the activity pattern model. The behavioral unit for this model is a person-day. In estimation and application we limit the sample to weekdays (Monday to Friday) for persons aged 16 and over. For each person we know individual and household characteristics, zone of residence, and numbers of household drivers and vehicles.

The model determines the purpose of the person's primary activity of the day, and whether it occurs at home or on a tour, allowing it to capture trade-offs between at-home and on-tour activities. The primary activity is one of six alternatives (subsistence (work or school) at home, subsistence on-tour, maintenance (shopping, personal business, etc.) at home, maintenance on tour, discretionary (social, recreation, entertainment, etc.) at home, and discretionary on-tour.)

If the primary activity is on-tour, the activity pattern model also determines the trip chain type for that tour (tour type), defined by the number and sequence of stops in the tour. Four tour types available for all tour purposes are: simple (no intermediate activities), one or more intermediate activities on the way from home to the primary destination, one or more intermediate activities on the way from the primary destination to home, and intermediate activities in both directions. For work/school tours, types 5-8 are defined as above with the addition of a work-based subtour.

Simultaneously with primary activity and primary tour type, the activity pattern model predicts the number and purposes of secondary tours. There are six alternatives (no secondary tours, one secondary tour for work or maintenance (SM), two or more secondary tours for work or maintenance (SMM), one secondary tour for discretionary purpose (SD), two or more secondary tours for discretionary purpose (SDD), two or more secondary tours with at least one for work or maintenance and at least one for discretionary purposes (SMD).)

Since not all of the tour types apply to all of the primary activity types, there are 8+1+4+1+4+1 = 19 possible combinations of primary activity/tour types. Each of the six secondary tour alternatives are possible for all primary activity/tour types, so the model has a total of 19 x 6 = 114 alternatives.

The utility function of each alternative in the multinomial logit model includes a logsum variable and parameter for each tour in the pattern. Parameter estimation results are given in Table 1, where a bold heading identifies a group of related parameters, usually indicating a subset of the alternatives to which the parameters apply. A parameter within a group usually captures market heterogeneity or alternative heterogeneity within the subset of alternatives.

Table 1: Day Activity Pattern Choice Model Estimation Results

Observations	14774	Rho-squared (0)	0.319
Final log(L)	-47622	Rho-squared (c)	0.089

Alternative / variable	Coeff.	T-st.
Mode / destination model logsums		
Work/school primary tour	0.182	6.5
Maintenance primary tour	0.045	1.9
Discretionary primary tour	0.104	3.3
Maintenance secondary tours	0.147	8.8
Discretionary secondary tours	0.047	4.3
WT-Work on tour variables		
Constant	-1.96	-6.5
Full time worker	3.13	39.6
Part time worker	2.67	27.9
Age under 20	2.11	15.2
Age 20-24	0.833	7.5
Age 25-34	0.246	4.0
Age 55-64	-0.398	-5.5
Age over 65	-1.68	-16.0
Female, 2+ adults in hh	-0.247	-4.3
Kids under 5 in hh	-0.406	-5.7
WH-Work at home variables		
Constant	-2.80	-16.1
Full time worker	2.30	14.8
Part time worker	2.28	12.6
Age over 65	-0.73	-3.6
Male, only adult in hh, worker	0.7659	4.5
Male, 2+ adults in hh	0.236	2.2
MT-Maintenance on tour variables		
Constant	-0.119	-0.5
Part time worker	0.229	2.3
Age under 20	-0.763	-4.4
Male, 2+ adults in hh	-0.371	-6.1
Female, kids under 12 in hh	0.320	4.1
No cars in hh	-0.008	-0.1
Fewer cars then adults in hh	-0.111	-1.4
MH-Maintenance at home variables		
Constant	0.215	2.6
Full time worker	-0.553	-5.1
Age under 20	-1.38	-4.1
Female, kids under 12 in hh	0.393	3.6
Female, 2+ adults in hh	0.489	6.0
DT-Discretionary on tour variables		
Constant	-0.686	-2.2
Full time worker	-0.315	-3.5
No cars in hh	-0.525	-3.1
Fewer cars then adults in hh	-0.417	-4.2
DH-Discretionary at home variables		
Income under $30,000	0.325	3.6
Income over $60,000	-0.226	-1.5
WT-Work on tour type constants		
Constant-stop on way to	-1.19	-23.0
Constant-stop on way back	-2.00	-37.6
Constant-stop both ways	-2.50	-30.7
Constant- no stops plus subtour	-1.99	-23.3
Constant, stop on way to & subtour	-3.03	-29.3
Constant, stop on way back & subtour	-3.90	-32.8
Constant,	-4.45	-31.8
WI- Work intermediate stop variables		
Income over $60,000	0.265	7.0
Age under 20	-0.311	-3.9
Age over 45	-0.087	-2.3
Female, kids under 12 in hh	0.624	12.3
Male, 2+ adults in hh, 1+ non-worker	-0.225	-4.2
Female, single, worker	0.246	4.3
No cars in hh	-0.268	-2.4
Fewer cars then adults in hh	-0.223	-4.4
WS-Work-based subtour variables		
Income over $60,000	0.272	4.3
Full time worker	0.543	6.7
Female, kids under 12 in hh	-0.353	-3.5
Male, single, worker	0.283	2.9
No cars in hh	-0.291	-1.6
Fewer cars then adults in hh	-0.155	-1.9
MT-Maintenance tour type constants		
Constant-stop on way to	-0.577	-8.2
Constant-stop on way back	-0.549	-8.5
Constant-stop both ways	-1.05	-10.8
MI-Maintenance intermediate stop variables		
Full time worker	-0.212	-3.2
Age over 65	-0.252	-4.4
No cars in hh	-0.664	-4.6
Fewer cars then adults in hh	-0.238	-3.2
DT-Discretionary tour type constants		
Constant-stop on way to	-1.41	-14.1
Constant-stop on way back	-1.46	-14.4
Constant-stop both ways	-1.82	-14.0
DI-Discretionary intermediate stop variables		
Age over 65	-0.361	-3.7
Male, 2+ adults in hh, 1+ non-worker	-0.389	-3.6
No cars in hh	-0.755	-2.5
Fewer cars then adults in hh	-0.196	-1.5
All purposes - additional variables		
Stop on way to- No kids in hh	0.194	4.3
Stop both ways- Kids under age 5 in hh	0.575	6.7
Secondary maintenance tour variables		
Full time worker	-0.168	-2.5
Part time worker	0.251	3.1
Female, no kids in hh	-0.181	-3.2
Age over 65	-0.354	-4.8
Female, kids in hh	0.488	7.3
Female, 2+ adults in hh, all workers	-0.022	-0.3
No cars in hh	-0.604	-4.6
Fewer cars then adults in hh	0.078	1.4
Secondary discretionary tour variables		
Age under 35	0.125	2.4
Full time worker	-0.284	-5.1
Age under 20	0.182	1.8
Age over 65	-0.284	-4.0
No cars in hh	-0.453	-3.7
Fewer cars then adults in hh	-0.232	-3.9
SM-1 secondary maintenance tour constants		
Primary = work/school on tour	-2.74	-16.0
Primary = work/school at home	-1.15	-5.6
Primary = maintenance on tour	-2.20	-12.9
Primary = maintenance at home	-3.01	-16.0
Primary = discretionary on tour	-3.19	-16.8
Primary = discretionary at home	-3.46	-16.2
Primary tour has 1 intermediate stop	-0.224	-3.9
Primary tour has 2 intermediate stops	-0.194	-2.0
Primary tour has a work-based subtour	-0.145	-1.7
SD-1 secondary discretionary tour constants		
Primary = work/school on tour	-1.63	-13.6
Primary = work/school at home	-0.705	-3.8
Primary = maintenance on tour	-1.04	-8.6

Primary = maintenance at home	-4.01	-14.7
Primary = discretionary on tour	-1.47	-11.2
Primary = discretionary at home	-4.70	-11.1
Primary tour has 1 intermediate stop	-0.234	-4.2
Primary tour has 2 intermediate stops	-0.457	-4.5
Primary tour has a work-based subtour	-0.071	-0.9
SMM-2+ secondary maintenance tours constants		
Primary = work/school on tour	-6.23	-18.6
Primary = work/school at home	-3.22	-9.2
Primary = maintenance on tour	-4.52	-13.8
Primary = maintenance at home	-5.08	-14.9
Primary = discretionary on tour	-6.07	-16.1
Primary = discretionary at home	-6.16	-15.0
Primary tour has 1 intermediate stop	-0.15	-1.3
Primary tour has 2 intermediate stops	-0.331	-1.6
Primary tour has a work-based subtour	-0.684	-2.5
SDD-2+ secondary discretionary tours constants		
Primary = work/school on tour	-5.42	-19.7
Primary = work/school at home	-2.70	-7.9
Primary = maintenance on tour	-3.11	-12.8
Primary = maintenance at home	-5	*
Primary = discretionary on tour	-3.60	-13.6
Primary = discretionary at home	-5	*
Primary tour has 1 intermediate stop	-0.222	-1.3
Primary tour has 2 intermediate stops	-0.734	-2.3
Primary tour has a work-based subtour	-0.187	-0.5
SMD-1+ maint. & 1+ discret. tours constants		
Primary = work/school on tour	-5.05	-22.4
Primary = work/school at home	-1.83	-7.5
Primary = maintenance on tour	-2.94	-13.9
Primary = maintenance at home	-6.70	-12.5
Primary = discretionary on tour	-4.47	-17.5
Primary = discretionary at home	-6.33	-11.8
Primary tour has 1 intermediate stop	-0.340	-3.1
Primary tour has 2 intermediate stops	-0.313	-1.9
Primary tour has a work-based subtour	-0.578	-2.2

The Home-based Tour Time of Day Models

Given the pattern, time of day models determine the sequencing and duration of its tours and the out-of-home activities that comprise them. We distinguish five time periods (3:00 to 6:59 am (Early or EA), 7:00 to 9:29 am (AM peak or AM), 9:30 am to 3:59 pm (Midday or MD), 4:00 to 6:59 pm (PM peak or PM), and 7:00 pm to 2:59 am (Late or LA).) For each tour, the time of day model predicts the combination of departure time from home and departure time from the primary activity. There are twenty five combinations of start and end periods. Pairs extending overnight are eliminated in application, leaving fifteen combinations (EA-EA, EA-AM, EA-MD, EA-PM, EA-LA, AM-AM, AM-MD, AM-PM, AM-LA, MD-MD, MD-PM, MD-LA, PM-PM, PM-LA, LA-LA.)

There are three time of day models, one each for work/school, maintenance, and discretionary tours. Various person and household variables are used as independent variables, as well as logsums from the lower level mode/destination choice models. Tour purpose and tour type are also used as variables, meaning that the time of day models are applied conditionally on the results of the day activity pattern model. These models take into account whether or not there are intermediate activities on the half tours, whether it is a primary tour or a secondary tour, and whether or not a work/school tour is also made during the day. Estimation results are shown in Table 2 for work/maintenance tours, with parameters again grouped by subset of alternatives. Space limitations preclude presentation of results for maintenance and discretionary tours. For these and other details not reported here, see Bradley, *et al* (1998).

The Home-based Tour Primary Destination and Mode Choice Models

Given the pattern and tour times of day, the model system predicts the primary mode and destination for each tour. In reality, separate trips on the same tour can use different modes. This occurs in 3% of the Portland survey tours, usually with auto drive alone in one direction and drive with passenger in the other. To include these cases in model estimation, a set of rules was used to translate all possible mode combinations into the 9 modeled modes (auto drive alone, auto drive with passenger, auto passenger, MAX (light rail) with auto access, MAX with walk access, bus with auto access, bus with walk access, bicycle, walk only.) Although it is not done here, the most important mode combinations could be explicitly modeled in the mode choice alternatives.

For destination choice, parameter estimation and model application use a sample of 21 zones for each tour, drawn from the full set of 1244. Sampled alternatives are weighted according to their sampling probability to achieve consistent estimates (see Ben-Akiva and Lerman, 1985.)

Table 2: Home-Based Work/School Tour Times of Day Choice Model

Alternative / variable	Coeff.	T-St.
Observations	7443	
Final log(L)	-12736	
Rho-squared (0)	0.368	
Rho-squared (c)	0.075	
Logsum variables		
Mode / destination choice logsum	0.175	3.3
1- Early combinations		
Constant- Early-Early	-3.07	-17.0
Constant- Early-AM peak	-3.17	-16.7
Constant- AM peak-AM peak	-5.08	-11.2
2- From home Early– from work Midday (EA—MD)		
Constant	-1.50	-8.1
No intermediate stops	-0.279	-3.1
Full time worker	1.41	9.2
Age under 35	-0.332	-3.4
Male, no children in hhld	0.668	6.5
Children over age 12 in hhld	0.725	5.5
Children under age 5 in hhld	0.520	3.8
3- Early - PM peak, Late (EA—PM , EA—LA)		
Constant- Early - PM peak	-3.03	-11.5
Constant- Early - Late	-5.46	-18.1
Intermediate stop on way back home	0.681	4.9
Full time worker	2.28	9.0
Male	0.61	5.6
4- AM peak – Midday (AM—MD)		
Constant	0.054	0.6
Intermediate stop on way from home	0.893	13.3
Age under 20	1.33	11.8
Male, children over 12 in hhld	0.485	4.2
Female, children in household	0.486	6.2
5- AM peak - PM peak (AM—PM)		
Intermediate stop on way back home	0.696	8.4
Full time worker	1.36	17.0
Household income over 60K	0.244	4.2
Female	0.146	2.5
6- AM peak – Late (AM—LA)		
Constant	-2.06	-9.2
No intermediate stops	0.498	2.2
Intermediate stop on way back home	1.75	7.0
Male, single worker	0.679	3.1
7- Midday – Midday (MD—MD)		
Constant	-1.04	-7.4
No intermediate stops	-0.818	-6.6
Part time worker	1.10	8.3
1+ non-working adult in hhld	0.69	5.5
8- Midday - PM peak (MD—PM)		
Constant	-1.55	-10.9
Intermediate stop on way back home	1.05	7.6
Part time worker	0.640	5.2
Male, no children in hhld	0.884	6.7
Female, no children in hhld	0.437	3.2
Household income under 30K	0.449	3.8
9 - Midday – Late (MD—LA)		
Constant	-1.82	-9.5
No intermediate stops	0.755	4.4
Intermediate stop on way back home	1.52	7.5
Age under 25	1.24	10.5
Male, no children in hhld	0.410	3.7
Household income under 30K	0.468	4.0
Household income over 60K	-0.593	-3.7
10 - Late combinations		
Constant - PM peak – PM peak	-4.69	-16.1
Constant - PM peak – Late	-2.89	-13.7
Constant - Late – Late	-3.67	-15.9
No intermediate stops	0.622	3.4
Part time worker	0.628	3.8
Age under 25	0.702	3.9
Male, no children in hhld	0.536	3.4
Female, children under 5 in hhld	1.20	5.0

The mode/destination models use household and person data as well as network distance, time and cost data. In the course of testing, it was found that the RP data would not support estimation of reasonable coefficients for both the time and cost variables for any of the tour purposes. This is probably due to the fact that both parking costs and traffic congestion are fairly low in Portland (at least at the level of definition in the data), meaning that both car costs and car travel times are strongly related to distance and thus highly correlated with each other. For this reason, the values of travel time are constrained to be equal to those estimated from the concurrent stated preference survey, shown in Table 3. This is done by using "generalized time" in the models, constructed as the sum of all time and cost variables, after expressing each in terms of its equivalent drive alone minutes. The utility functions include linear, quadratic and cubic terms for this generalized time. The results are highly significant, with the same general shape in all the models. The function is slightly S-shaped, with disutility rising sharply at first, then leveling off a bit, and then rising more sharply again at very high travel times. When the model is applied to the estimation data set, the function gives a reasonable match to the actual distribution of tour distances in the data for all modes. Other mode-specific variables in the models are mostly related to age, gender and household type. The effect of car availability is very strong, particularly for the car driver and transit alternatives. Parameter estimates for the work/school tour model are in Table 4.

Table 3: Values of Time Estimated from Stated Preference Data

Type of travel time	Home to Work Travel			Home to Other Travel		
	Annual Household Income			Annual Household Income		
	Less than $30,000	$30-60,000	More than $60,000	Less than $30,000	$30-60,000	More than $60,000
Drive alone In-vehicle	8.9	12.3	17.7	12.2	12.2	23.7
Drive w/pass. In-vehicle	9.4	13.1	18.8	7.9	7.9	15.3
Transit In-vehicle	5.8	8.1	11.6	1.6	1.6	3.1
Transit Walk	21.5	29.7	42.8	29.4	29.4	56.9
Transit Headway	4.9	6.8	9.8	9.8	9.8	19.0
Transit Boardings	39.0	53.9	77.8	75.0	75.0	145.2

(All values in cents per minute, except for Transit Boardings)

Table 4: Home-Based Work/School Tour Mode/Destination Choice Models

Observations	7353
Final log(L)	-23455.8
Rho-squared (0)	0.335

Alternative / variable	Coeff.	T-st.
Car and transit modes		
SP-based generalized time (min)	-0.0667	-23.2
SP-based generalized time squared	3.52E-04	8.3
SP-based generalized time cubed	-1.10E-06	-6.3
Drive alone		
Car competition in hhld*	-1.98	-19.5
Age under 20	-1.29	-9.7
Age over 45	0.295	3.9
Children under age 5 in hhld	0.294	2.7
Fem. in 2+ adlt HH w 1+ non-wrker	-0.448	-3.6
2+ adults in household, all workers	0.185	2.3
No intermediate stops	-0.693	-9.3
Leave home before AM peak	-0.265	-2.1
Leave home during AM peak	-0.166	-1.9
Drive with passenger		
Constant	-3.33	-16.4
Log of distance (miles)	-0.434	-10.6
Car competition in hhld*	-0.905	-5.1
Age under 25	-0.334	-1.8
Male	0.651	4.6
Female, children under 5 in hhld	1.32	6.1
Male in 2+ adlt HH w 1+ non-wrker	-1.03	-4.3
Single adult, no children in hhld	-1.81	-4.9
Intermed. stop on way from home	1.01	7.5
Intermed. stop on way back home	0.812	5.6
Car passenger		
Constant	-2.67	-15.5
Age under 25	0.618	4.7
Female	0.375	3.5
Single adult	-0.905	-4.9
Leave home before AM peak	-0.558	-3.0
Return home after PM peak	-0.622	-3.4
Transit with walk access		
Constant	-4.54	-7.3
MAX LRT constant	-0.319	-2.1
No car in household	1.05	5.9
Hhld w/in ¼mi. of transit, orig. zone	1.73	6.4
Empl w/in ¼mi. of transit, dest. zone	1.88	3.2
Park and ride		
Constant	-4.55	-3.8
MAX LRT constant	-0.319	-2.1
Car competition in hhld*	-0.887	-3.5
Return home after PM peak	-2.35	-3.3
Mixed use w/in ½mi. of dest. zone	3.14E-04	4.8
Empl. w/in ¼mi of transit, dest. zone	2.22	1.8
Bicycle		
Constant	-3.24	-10.2
Travel time (min)	-0.0973	-6.2
Travel time squared	4.88E-04	2.2
Travel time cubed	-9.95E-07	-1.3
Female	-0.940	-4.0
Mixed use w/in ½ mi. of dest. zone	2.12E-04	2.7
Walk only		
Constant	-1.50	-7.0
Travel time (min)	-0.042	-19.9
Age under 20	0.708	3.3
Age under 35	0.421	2.8
Mixed use within ½mi. of dest zone	2.78E-04	5.0
Origin zone dummy	0.491	2.5
Destination land use		
Origin zone dummy	0.362	3.4
Employment within half-mile radius	3.55E-05	18.0
Retail empl. within half-mile radius	-1.91E-04	-10.0
Fraction of land used for recreation	1.16	7.6
Log of relevant size variable**	1.0	constr

* Car competition means <1 vehicle per worker for work/school, <1 vehicle per adult for other purposes.
** Size variables are total employment for work/school tours, retail + service employment for maintenance tours and retail + service emp.+ households for discretionary tours.

The Work-based Subtour and Intermediate Stop Models

No models predict work-based subtour time of day. Instead, fixed fractions are used, based on shares observed in the survey data. As expected, the time of day fractions are strongly correlated with the times of day the work tour begins and ends. The work-based subtour mode-destination choice model is very similar to the models for home-based tours described above, except now the choices are dependent on the mode used to go between home and work.

The "lowest" level model in the system determines the location for each intermediate activity made during a given half tour. The structure, sampling procedure and model specification is analogous to those of the mode/destination models described above, with two differences. First, the model is conditioned by all other tour and work subtour decisions, and takes the tour mode as given. Second, the travel costs, times and distances used in the utility functions and for sampling of alternatives include only the extra amount required to make the stop relative to making no intermediate stop on the half tour. For subtour and intermediate stop model estimation results, see Bradley, *et el* (1998).

APPLICATION OF THE MODELS

Figure 4 illustrates how the activity-based model system fits in the larger Portland forecasting system. Using (a) exogenous data for the base and policy cases, (b) a synthetic disaggregate population for each forecast year/ demographic scenario, and (c) assumed network performance attributes, the demand model generates a set of trip matrices. Network models assign the trips to the relevant networks and update the network attributes. The demand and network models are iterated until the network travel time attributes are consistent in all of the component models.

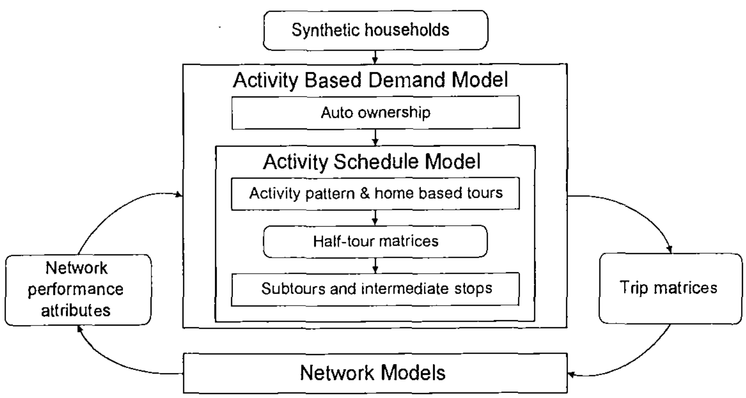

Figure 4: Model Application

The demand model consists of an auto ownership model plus the activity schedule model described in this paper. Within the activity schedule model, aggregate application methods are used for the conditional work-based subtour and intermediate stop components to reduce computer run time. This prevents the use of logsums in the home-based tour models that would otherwise capture the influence of expected utility from extra stops on the tour mode and primary destination choices.

The disaggregate component, including the activity pattern and home-based tour models, predicts activity schedule probabilities for each person, and aggregates them into a set of half-tour matrices that provide a count of time-period and mode specific half tours between all pairs of zones. Since secondary tour types are not modeled explicitly, tour type fractions from the survey data are applied to each predicted secondary tour. Also, some of the secondary tour alternatives do not exactly describe the number of secondary tours, so we make them exact during application by using average values from the survey sample.

The aggregate component of the activity schedule model adds work subtours to the half tour matrices using the predictions of the work subtour model and translates each half tour into chained or unchained trips using the predictions of the intermediate stop model. To do this, the work-based subtour models are applied to the predicted zonal totals of work stops for each of several market segments. Likewise the intermediate stop models are applied to the zone-to-zone totals of half tours for each of the market segments.

Illustrative results

The first model application at Portland Metro is to provide forecasts for possible congestion pricing initiatives. Application results for the entire model system are not yet available, so Table 5 shows results from applying the disaggregate portion of the activity schedule model to the survey data. What are not included in this example are the generation of the synthetic population, the aggregate component of the activity schedule model, and the network assignment procedure. We focus here on the relative policy effects on mode, trip distance, time of day, and activity participation. Results are given for three policies, each with respect to the base case 1994 road and transit networks.

Table 5: Model application—percent changes in tour production and travel miles under three policy scenarios

	10 % increase in all auto travel time		100% increase in all variable auto costs		100% increase in peak period auto variable costs	
Subsistence (work/school) tours	**% change Tours**	**% change Miles**	**% change Tours**	**% change Miles**	**% change Tours**	**% change Miles**
All modes						
- All times of day	-0.2	-2.7	-0.8	-9.4	-0.6	-5.5
- AM peak	-0.3	-2.9	-0.6	-9.0	-1.6	-8.6
- Midday	-0.2	-2.6	-1.1	-9.8	+0.8	-1.2
- PM peak	-0.2	-2.8	-0.6	-9.0	-1.8	-9.1
- Off-peak	-0.1	-2.3	-1.2	-10.1	+1.6	+0.6
Single occupant auto						
- All times of day	-1.3	-3.6	-5.8	-14.6	-3.5	-8.5
- AM peak	-1.4	-4.0	-5.8	-14.6	-5.9	-13.1
- Midday	-1.2	-3.3	-6.2	-15.0	-0.4	-2.5
- PM peak	-1.4	-3.9	-5.6	-14.4	-6.1	-13.6
- Off-peak	-1.0	-2.9	-5.9	-14.5	+1.0	0.0
Maintenance tours	**% change Tours**	**% change Miles**	**% change Tours**	**% change Miles**	**% change Tours**	**% change Miles**
All modes						
- All times of day	-1.0	-5.0	-2.3	-14.2	0.0	-2.1
- AM peak	-1.0	-5.2	-2.0	-13.6	-1.7	-8.0
- Midday	-0.7	-4.6	-1.6	-13.7	+0.8	0.0
- PM peak	-1.4	-5.5	-2.9	-14.3	-1.6	-6.6
- Off-peak	-1.6	-5.3	-4.0	-15.9	+0.5	+0.5
Single occupant auto						
- All times of day	-2.8	-6.5	-8.7	-21.5	-1.2	-3.6
- AM peak	-2.5	-6.6	-6.9	-19.3	-4.2	-11.0
- Midday	-2.5	-6.2	-8.2	-21.4	+0.3	-0.7
- PM peak	-3.3	-7.2	-9.6	-21.9	-4.5	-10.2
- Off-peak	-3.4	-6.8	-10.7	-23.5	+0.4	+0.4
Discretionary tours	**% change Tours**	**% change Miles**	**% change Tours**	**% change Miles**	**% change Tours**	**% change Miles**
All modes						
- All times of day	-0.3	-4.4	-0.6	-13.3	+0.2	-1.2
- AM peak	-0.2	-4.3	-0.2	-11.9	-1.4	-7.8
- Midday	-0.2	-4.3	-0.3	-13.2	+0.6	-0.8
- PM peak	-0.3	-4.6	-0.5	-12.9	-0.3	-2.9
- Off-peak	-0.3	-4.5	-0.9	-14.0	+0.6	+0.7
Single occupant auto						
- All times of day	-3.1	-6.5	-10.7	-23.1	-1.3	-3.2
- AM peak	-2.5	-6.4	-7.9	-20.4	-5.5	-12.5
- Midday	-2.9	-6.4	-10.0	-22.6	-0.6	-2.2
- PM peak	-3.3	-6.7	-11.1	-23.3	-3.1	-6.4
- Off-peak	-3.2	-6.4	-11.9	-24.3	+0.6	+0.6

For the first policy, a 10% increase in all car travel times, the results show a work/school mode choice elasticity for car drive alone tours of -0.13, and for drive alone tour distance of -0.36. This indicates that the destination choice element is more sensitive than the mode choice element for this policy. (This must be interpreted as a longer-term elasticity, since people cannot easily change their work or school destinations in the short term.) For maintenance and discretionary tours, the car drive alone tour and distance elasticities with respect to travel time appear higher than for work/school, with values around -0.30 and -0.65 respectively. For all tour purposes, the effects on car drive alone tours are about the same for all periods of the day.

For the first policy, the decrease in the number of total tours across all modes and all times of day is about -0.2% for work/school, -1.0% for maintenance and -0.3% for discretionary. This indicates the travel suppression and/or trip chaining effects of the policy, which are predicted via the activity pattern model. As expected, this effect is smaller than the mode choice or destination choice effects. The fraction of tours suppressed is about the same during all periods of the day.

The second policy simulates a 100% increase in car fuel and operating costs, from 8 to 16 cents per mile. The implied elasticities for car drive alone in this case are about -0.06 and -0.15 for work/school tours and mileage, and about -0.10 and -0.21 for both maintenance and discretionary tours and mileage. Again, effects are similar for all periods of the day. A difference with respect to the travel time policy is that increasing car costs causes an increase in multiple occupant car tours, whereas increasing car travel times causes a decrease in all types of car tours.

The third policy simulates a toll charged only during the AM and PM peak periods, which has the effect of doubling the car fuel and operating costs during those periods (i.e. it is equivalent to the second policy, but applied only during the peaks). Table 5 shows that there is some shift of tours out of the peak periods into the midday and off-peak periods. To offset the off-peak increase, some tours that previously had one half tour in one of the peak periods and the other half tour outside the peak may now switch modes or destinations or be suppressed altogether. For work/school car driver tours, the net effect from these two offsetting changes is negative in the midday period (-0.4%) and positive in the early and late off-peak periods (+1.0%). The results for maintenance and discretionary tours are similar to those for work/school. Modeling tours explicitly with time of day sensitivity allows the models to capture such complex shifts.

There are also offsetting changes predicted by the activity pattern model. When some activities with peak period travel are suppressed, this allows other activities to be substituted during the midday and off-peak periods when travel costs have not increased. These new activities in the off-peak periods tend to be non-work activities, some of which would have otherwise been made as intermediate stops on a work tour. For maintenance, these types of changes cancel each other out (net effect of 0), while for discretionary there is even a slight increase in the total number of tours made (+0.2%). In summary, in addition to suppressing travel, the model predicts activity substitution, time of day shifts and induced leisure travel demand. Although these changes are not large in this example, they illustrate the type of realistic policy effects added by adopting the activity-based modeling approach.

EVALUATION AND CONCLUSIONS

The day activity schedule model, as implemented in Portland, retains some weaknesses. We group these into five categories, including incompleteness, coarse schedule resolution, and misspecification of utility functions, model structure and availability. Incompleteness means that some activities are not explicitly modeled. The model misses interactions in the individual's behavior between modeled and unmodeled activities. The Portland model does not include at-home activities except for the primary activity. It therefore inadequately captures interactions between at-home and out-of-home activity participation. Including at-home activities is straightforward, although availability, definition and accuracy of at-home activities comprise an important data collection issue.

Coarse resolution of the schedule is caused by aggregating discrete alternatives and discretizing continuous choice variables, such as time, into large categories. This prevents the model from capturing variation in behavior when it masks heterogeneity of disaggregate alternatives. In the Portland model aggregation occurs in several dimensions, including activity purposes (subsistence, maintenance, discretionary), tour type (does not identify multiple stops or purposes on subtours and intermediate stops), mode (few mixed mode alternatives), destination (traditional zonal aggregation) and time of day (five time periods). Refining resolution can substantially increase model size and the need for detailed spatial and time-specific location and travel characteristics. The standard method of handling large choice sets, alternative sampling, is used for destination choices, and might be used to handle fine resolution of destination and time of day dimensions, with potentially significant improvements in model performance. For other dimensions, the continued rapid advance in computing technology should enable model improvement by judicious refinement of resolution.

Misspecification of the utility functions occurs when important variables are missing or the functional form is incorrect, causing prediction bias and policy insensitivity. In the Portland model, measures of expected utility from the conditional subtour and intermediate stop models are excluded from the tour models for the sake of computational speed, reducing the model's accuracy in predicting trip chaining behavior. Other misspecification is probably also present because our understanding of the factors affecting choice is still incomplete.

Four types of structural misspecification may be present, potentially distorting cross elasticities and causing prediction bias. First, we may group two or more dimensions—such as mode and destination choice, or multiple dimensions of the activity pattern—on one level of the model, when they should be nested because of shared unobserved attributes in one dimension. Second, we may incorrectly treat two components of the choice—such as primary and secondary tours—as conditionally independent when their availability or utilities are really correlated. Third, we may nest two dimensions—such as conditioning work mode choice on timing—when the opposite nesting is more appropriate. Fourth, we may rely on a nested structure when shared unobserved attributes in two or more dimensions call for a more complex form than nested logit.

Misspecification of availability primarily involves including alternatives when they are infeasible or not considered in the decision, resulting in biased predictions. In many cases, availability can be approximated by using deterministic rules—such as limiting work patterns to employed persons. But it is difficult to capture all important availability restrictions. For example, in the Portland model, assumed conditional independence of primary and secondary tours makes it impossible to prevent the prediction of primary and secondary tours occurring during overlapping time periods.

Despite these weaknesses, the day activity schedule model implemented in Portland represents an important improvement over trip and tour-based models in use today. It provides a more advanced activity-based representation of travel behavior in an operational general purpose metropolitan travel forecasting model system, including the ability to capture changes in activity participation, trip chaining, inter-tour and at-home vs on-tour trade-offs, as well as changes in timing, mode and destination. Preliminary application results demonstrate the aggregate effects of these complex behavior changes. Many of the weaknesses described above arise primarily from technology limits and incomplete knowledge of the decision process, which can both be dealt with as the model is used in policy studies and enhanced through further research and development.

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