Kitamura, R. and S. Fujii (1998) Two computational process models of activity-travel behavior. In T. Garling, T. Laitila and K. Westin (eds.) Theoretical Foundations of Travel Choice Modeling, pp. 251-279.

TWO COMPUTATIONAL PROCESS MODELS OF ACTIVITY-TRAVEL BEHAVIOR[1]

Ryuichi Kitamura and Satoshi Fujii
Department of Civil Engineering Systems
Graduate School of Engineering
Kyoto University
Sakyo-ku, Kyoto 606-01
Japan

1. INTRODUCTION

The ultimate goal of travel behavior analysis is to gain a full understanding of why people travel and to develop quantitative capabilities that facilitate the prediction of travel behavior. Toward this end, the individual's travel behavior has been examined in connection with her activity engagement, with the recognition that travel demand is a derived demand. Studies from this viewpoint are referred to as "activity-based analyses of travel behavior" (for reviews, see Damm 1983; Jones et al., 1983; Kitamura, 1988; Jones et al., 1990; Axhausen & Gärling, 1992; Gärling et al., 1994; Ettema, 1996; and Kurani and Kitamura, 1996). Along with the recent developments of micro-simulation model systems of travel behavior, the activity-based analysis of travel behavior is now entering the stage of large-scale application to travel demand forecasting and policy analysis. This is of particular significance because of the following shifts in the focus of urban transportation planning.

The first is the shift away from facility construction toward transportation systems management (TSM) and toward travel demand management (TDM) – attempts to resolve transportation problems by better operating existing facilities and managing travel demand, rather than building more facilities. Tools currently available for passenger travel demand forecasting and policy analysis are mostly derived from the trip-based, four-step procedure, developed in the 1950's and 1960's when urban population was growing rapidly, motorization was progressing, and suburban sprawling was starting. Not surprisingly, these tools, geared towards the planning needs of decades ago, are not well suited to address current planning issues. In particular, they are mostly not applicable to the evaluation of the effectiveness of TDM measures that are extensive, sophisticated, and fine-tuned to target specific traveler segments.

Another important shift is the recent emphasis on the environmental impact of vehicular transportation. Increasing skepticism surrounds the notion that pollutant emissions from road traffic can be reduced by expanding road capacity and thereby improving traffic flow. At the same time, there have been increasing concerns with new trips induced by capacity addition. If travel demand follows the economic demand-supply relationship, and if the primary cost

[1] Parts of this study were presented earlier at the U.S. Federal Highway Administration's Travel Model Improvement Program (TMIP) conference on Activity-based Travel Forecasting, New Orleans, June, 1996.

component of travel is the time cost, then reduced travel time due to capacity addition would increase the demand for travel; people would then travel more often and for longer distances.

If an increase of transportation capacity induces new trips, then they must be accurately reflected in the environmental impact assessment; otherwise environmental impacts will always be under-estimated. No effective methods, however, have been established for the assessment of the magnitude and characteristics of induced trips, especially for induced trips in narrower sense, i.e., those trips that were not made before but are newly made due to improved travel condition. While one may be tempted to develop an aggregate demand function that expresses travel demand as a function of network service levels, it is doubtful if such a function can fully represent various constraints and thresholds that govern individuals' activity engagement and trip making.

Quite important is to recognize that capacity addition and TDM and other current policy measures both have far-reaching impacts on urban residents' daily life. This is more so with TDM measures than with traditional, supply-oriented measures. For example, flexible work hours, compressed work weeks, or telecommuting all affect how a worker allocates time to different activities within each day and across weekdays and weekend days. Trip-based models are inadequate for the assessment of the effectiveness of such measures. Practical, activity-based models are called for.

One of the approaches taken to modeling activity engagement and scheduling behavior is to apply *computational process models*, of which *production systems* are one example, to the problem of how people formulate and execute schedules. The approach is reviewed in Kurani and Kitamura (1996) as:

> "Tasker and Axhausen (1994) describe the computational process approach as one in which the decision maker '… tries a sequence of possibilities and selects the first one that is suitable.' They differentiate between such models based on a search process from utility based models, stating:
>
> > 'Firstly, the search process is a computational process, not a mathematical function. Thus, the order in which heuristic functions for various modes in the tree are evaluated affects the way the search is conducted, and its final result. Calculations involving utility, however, optimize in a sequence independent manner.
> >
> > 'Secondly, heuristics can be represented, not just as a scalar, but as a vector of quantities (time, money, safety, comfort, social obligation, etc., along with risk elements for each of these where appropriate), …' (ibid.).
>
> "Production models were developed by Newell and Simon (1972) as models of human problem solving. The production system consists of a set of rules, or condition-action pairs that specify an action to be executed when a condition is met. Computational process models are themselves an example of a physical symbol system:
>
> > '… capable of inputting, outputting, storing, and modifying symbol structures, and of carrying out some of these actions in response to the symbols themselves. 'Symbols' are any kinds of patterns on which these operations can be performed, where some of the patterns denote actions (that is, serve as commands or instructions)' (Simon, 1990)."

Presented in this paper are two computational process models of activity-travel behavior: the Prism-Constrained Activity-Travel Simulator (PCATS) and Activity-Mobility Simulator (AMOS). PCATS (Kitamura et al., 1996a) is a model system of activity engagement and travel, which incorporates the concept of Hägerstrand's time-space prism and generates activities and trips within prisms. Coupling constraints in an individual's daily itinerary are first identified in PCATS and prisms are established in the time-space dimension. The choices of activity type, duration, location, and travel mode are then simulated sequentially while considering the prism constraints. Model components to simulate these choices are estimated using the results of a time-use survey conducted in the Osaka-Kobe metropolitan area of Japan, where PCATS has been implemented using network and land use data from the area. The impacts on activity-travel behavior of (a) increased travel time due to worsening congestion, and (b) change in work schedules, are assessed using the model system.

AMOS (Kitamura et al., 1993, 1995b), on the other hand, focuses on the individual's adaptation behavior. It is a simulation model system which has been developed primarily to evaluate the effectiveness of TDM measures, by replicating how a traveler would modify her activity and travel when a change takes place in the travel environment, e.g., an increase in auto travel cost and reduction in travel time due to congestion pricing. AMOS takes an observed ("baseline") daily travel pattern of an individual; generates an adaptation option (e.g., change commute travel mode) that may be adopted by the individual when faced with the change in the travel environment; adjusts the baseline pattern (e.g., re-sequence activities, select new destinations) to produce a modified activity-travel pattern; evaluates the utility of the modified pattern; based on a satisficing rule, accepts one of the modified patterns so far generated and terminates the search, or continues to search for alternatives. An AMOS prototype has been implemented in the Washington, D.C., metropolitan area (Kitamura et al., 1995b; RDC, 1995). Because all TDM measures considered in the implementation project are aimed at commuters, the current prototype is formulated for commuters only.[2]

In the next section, the outline of PCATS is presented. This is followed by the presentation of scenario analysis results in Section 3. A brief summary of PCATS is given in Section 4. The components of AMOS are described in Section 5. Discussed in Section 6 are AMOS model implementation efforts and results of scenario analyses to evaluate TDM effectiveness. A summary on AMOS is given in Section 7. Section 8 offers conclusions.

2. OVERVIEW OF PCATS[3]

The individual's activity engagement and travel are simulated by PCATS within constraints as embodied by Hägerstrand's prisms. In defining prisms for each individual, it is assumed that the simulation period, say a day, can be divided into periods of two types: *open periods* and *blocked periods*. Open periods are ones in which the individual has the option of traveling and engaging in activities. In blocked periods, on the other hand, the individual is committed to engage in certain activities at certain locations. Activities participated within a blocked period

---

[2] For details, see RDC (1995) and Pendyala et al. (1996). AMOS is currently extended to include both commuters and non-commuters.

[3] The description of PCATS in Sections 2 through 4 draws from Kitamura et al. (1996a).

will be called *fixed activities*; those pursued in an open period *flexible activities*.[4] Given the speed of travel, the ending time and location of a blocked period and the beginning time and location of the subsequent blocked period together define a time-space prism in which the individual's activity and travel must be contained.

It is assumed that the individual's activity decision is dependent on the past, but not dependent on the future, except for the presence of prism constraints. It is further assumed that activity engagement decision is made sequentially, conditioned upon past activity engagement. This depiction of decision structure in PCATS is based on the identity discussed below.

2.1. Overall Structure

The individual's decision within a open period is depicted in PCATS as shown in Figure 1. The characterization found in the figure is based on a certain decomposition of activity-travel decision into a series of conditional choices. A few notes about this decomposition are due prior to the discussion of the figure. As aspects of activity-travel decision, consider: activity type, activity duration, location, and travel mode (if applicable). Let

$$
\begin{aligned}
X_n &= \text{the type of the n-th activity,} \\
D_n &= \text{the duration of the n-th activity,} \\
L_n &= \text{the location of the n-th activity,} \\
M_n &= \text{the mode of travel used to reach the location of the n-th activity,} \\
\mathbf{X} &= (X_0, X_1, \ldots, X_k), \\
\mathbf{D} &= (D_0, D_1, \ldots, D_k), \\
\mathbf{L} &= (L_0, L_1, \ldots, L_k), \\
\mathbf{M} &= (M_0, M_1, \ldots, M_k), \text{ and} \\
k &= \text{total number of activities during the study period.}
\end{aligned}
$$

Then the vectors, ($\mathbf{X}$, $\mathbf{D}$, $\mathbf{L}$, $\mathbf{M}$), define the individual's activity-travel patterns, starting with the initial condition, (X_0, D_0, L_0, M_0), and ending with the final activity, (X_k, D_k, L_k, M_k). If one can define Pr[$\mathbf{X}$, $\mathbf{D}$, $\mathbf{L}$, $\mathbf{M}$] for any ($\mathbf{X}$, $\mathbf{D}$, $\mathbf{L}$, $\mathbf{M}$), then complete probabilistic characterization of activity-travel patterns is achieved. This probability, however, is overly complex. The approach taken in PCATS is to adopt the following decomposition:

$$
\begin{aligned}
&\Pr[\mathbf{X}, \mathbf{D}, \mathbf{L}, \mathbf{M}] \\
&\quad \equiv \Pr[X_k, D_k, L_k, M_k | \tilde{X}_{k-1}, \tilde{D}_{k-1}, \tilde{L}_{k-1}, \tilde{M}_{n-1}] \\
&\qquad \times \Pr[X_{k-1}, D_{k-1}, L_{k-1}, M_{k-1} | \tilde{X}_{k-2}, \tilde{D}_{k-2}, \tilde{L}_{k-2}, \tilde{M}_{n-2}] \times \ldots \\
&\qquad \times \Pr[X_1, D_1, L_1, M_1 | X_0, D_0, L_0, M_0]
\end{aligned}
$$

[4] The activity categories used in PCATS are: sleep, personal care (other than taking bath), personal care (bath), child care, meal, domestic chore, work and work-related, school and study, social, grocery shopping, comparison shopping, hobbies and entertainment, sports and exercises, TV viewing, reading, resting, medical and dental, and others. A set of assumptions are adopted to determine whether an activity is fixed or flexible. Sleep is always classified as a fixed activity. Personal care (other than taking bath), personal care (bath), TV viewing, reading, and resting, on the other hand, are always classified as flexible. Activities of the remaining types are classified as fixed if the respondent indicated in the survey that the activity was subject to both temporal and spatial constraints; otherwise they are regarded to be flexible.

where

$$\tilde{X}_{n-1} = (X_0, X_1, X_2, ..., X_{n-1}),$$
$$\tilde{D}_{n-1} = (D_0, D_1, D_2, ..., D_{n-1}),$$
$$\tilde{L}_{n-1} = (L_0, L_1, L_2, ..., L_{n-1}), \text{ and}$$
$$\tilde{M}_{n-1} = (M_0, M_1, M_2, ..., M_{n-1}).$$

Namely, the simultaneous probability associated with (**X**, **D**, **L**, **M**) is decomposed into a series of conditional probabilities associated with (X_n, D_n, L_n, M_n), given the past history, ($\tilde{X}_{n-1}$, $\tilde{D}_{n-1}$, $\tilde{L}_{n-1}$, $\tilde{M}_{n-1}$), n = 1, 2, …, k.

To be explicit about the time of day, consider the following expression:

$$\Pr[X_n, D_n, L_n, M_n | t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}], \quad n = 1, 2, ..., k$$

where

t_{n-1} = the completion time of the (n-1)-th activity,
$\tilde{R}_{n-1}$ = (R_0, R_1, R_2, ..., R_{n-1}), and
R_n = the travel time to reach the n-th activity location (0 if no travel is involved).

This probability is unity if the n-th activity is in a blocked period. No attempt is required to develop a model for the probability in this case. The initial state at time t_0 is defined by (X_0, D_0, L_0, M_0, R_0). The first activity may be the continuation of the 0-th activity (this is an exception and no subsequent activity for n = 2, 3, ..., k, will be a continuation of the preceding activity).

R_n is not treated as a random variable in PCATS; it is assumed that the travel time is deterministic given the travel mode used and the origin and destination of the trip (M_n, L_{n-1}, and L_n). The activity completion time, t_{n-1}, can be uniquely determined given $\tilde{D}_{n-1}$ and $\tilde{R}_{n-1}$.

The joint probability associated with the attributes of the n-th activity can be further decomposed into many (in this case 4! = 24) different sequences of conditional probabilities. For example,

$$\begin{aligned}
&\Pr[X_n, D_n, L_n, M_n | t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \\
&\quad = \Pr[X_n | t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \times \Pr[D_n | X_n; t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \\
&\qquad \times \Pr[L_n | X_n, D_n; t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \\
&\qquad \times \Pr[M_n | X_n, D_n, L_n; t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \\
&\quad = \Pr[D_n | t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \times \Pr[X_n | D_n; t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \\
&\qquad \times \Pr[M_n | D_n, X_n; t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}] \\
&\qquad \times \Pr[L_n | D_n, X_n, M_n; t_{n-1}, \tilde{X}_{n-1}, \tilde{D}_{n-1}, \tilde{L}_{n-1}, \tilde{M}_{n-1}, \tilde{R}_{n-1}], \text{ etc.}
\end{aligned}$$

The identities imply that there will be many different sequential models for (X_n, D_n, L_n, M_n), and that these sequential models will all offer in principle the same statistical fit to the data. Then a particular sequential model may be preferred and selected considering theoretical support, policy sensitivity, and ease of modeling. The sequence adopted in the development of PCATS is $X_n \rightarrow L_n \rightarrow M_n \rightarrow D_n$.

2.2. Activity Type Choice Model

The activity type choice model is formulated as a nested-logit model with a two-tier structure. Exactly which alternatives can be included in the choice set is determined considering prism constraints. Namely, the formation of choice sets in PCATS is governed in part by prism constraints.

In the first (upper) tier, one of the following three broad classes of activities is chosen:

- in-home activity,
- activity at (or near) the location of the next fixed activity, and
- general out-of-home activity.

The second tier under “in-home activity” includes:

- engage in out-of-home activity subsequently, and
- do not engage in out-of-home activity

within the current open period. If the former is the case, then the duration of the in-home activity is determined (see Section 2.4), and the activity choice model is applied again to simulate the next, out-of-home activity, with the “in-home activity” alternative excluded from the choice set. If the latter is the case, then the travel to the location of the next fixed activity is simulated. Likewise, if the option of “activity at (or near) the location of the next fixed activity” is selected in the first tier, then the travel to the next fixed location will be simulated.

If “general out-of-home activity” is chosen, then the activity type is selected in the second tier. Activities classified into the following six activity types comprise the choice set in the second tier:

- meal,
- social,
- grocery shopping,
- comparison shopping,
- hobbies and entertainment, and
- sports and exercises.

The explanatory variables used to model the choice of out-of-home activity type include:

- personal attributes: age, sex, home-maker or not,
- time of day, and
- probability that the activity duration fits within the open period.

The last variable is defined as

$$\Pr[Z \le D_f | X_n = j] = F_j(D_f | S_{ji})$$

where

Z = activity duration,
D_f = $T_s - t_{n-1} - R_s$,
T_s = the beginning time of the next fixed activity,
R_s = travel time to the location of the next fixed activity using the fastest travel mode that is available,
F_j = the cumulative distribution function of activity durations for activity type j, and
S_{ji} = a vector of explanatory variables for activity type j and individual i.

Coefficient estimates of this variable indicate the anticipated tendency that activities which are less likely to fit within an open period tend not to be pursued; see Otsuka (1996).

2.3. Destination and Mode Choice Model

The destination and mode choice model is formulated also as a nested-logit model. The first tier concerns the choice of destination, and the second tier the conditional choice of travel mode, given the destination. In the current version of PCATS, one model is applied to all trips; this is restrictive and in the future models will be differentiated by trip purpose. Municipalities are used as the unit of geographical aggregation in this study. Travel modes are classified into {public transit, automobile, bicycle, walk}. The uncertainty in the choice set is represented during the model estimation using the method outlined in Ben-Akiva & Lerman (1985)

The explanatory variables used in the model are:

Destination Choice
- zonal population,
- number of commercial establishments,
- intra-zone destination dummy,
- the possible minimum travel time to the destination zone, then to the location of the next fixed activity, and
- probability that the activity duration will fit within the open period given the activity is pursued at the destination zone[5];

Conditional Mode Choice, Given Destination
- person and household attributes: age, sex, employment status, driver's license holding, household income, number of vehicles available,
- time of day,
- travel time and cost by mode, and number of transfers,
- intra-zone trip dummy, and

[5] Evaluated as in Section 2.2.

- location type indicator: indicators of the combination of the current location type and the location of the next fixed activity.

The coefficient estimates obtained all have expected signs and are significant.

This model is used in PCATS to generate a destination and mode for each trip. As is the case for activity choice, only those destination-mode pairs that are feasible under prism constraints and other coupling constraints (primarily for auto availability), are included in the choice set.

2.4. Activity Duration Models

The distribution of durations of flexible activities is determined by activity type, assuming that the parameters of the distribution (the mean and a shape parameter) are a function of personal attributes and other explanatory variables. Weibull distributions are exclusively used in the current version of PCATS. The explanatory variables used in the duration models are:

- person and household attributes: age, sex, employment, household income, driver's license holding, number of vehicles available;
- past activity engagement: the cumulative amount of time spent on the same type of activity since t_0;
- time of day: the mid-point of the time when the activity (including travel) starts (t_{n-1}) and the beginning time of the next fixed activity; the time in-home activity can start if returned home;
- time availability: the amount of time between the completion time of the previous activity and the beginning time of the next fixed activity; and
- location type indicator: indicators of the combination of the current location type and the location type of the next fixed activity.

The location types used here are {home, non-home}. Using these explanatory variables, duration models are estimated by the maximum likelihood method.[6] The results can be found in Otsuka (1996).

The activity duration models described above are used to determine the duration of the activity, given its type, location, the mode used to reach the activity location, and while considering prism constraints. The maximum possible activity duration is first determined based on the size of the prism, which is a function of the speed of travel, the location of the trip origin, the location of the activity, and the location of the next fixed activity. Then the distribution as given by the duration model for the activity type is truncated at the maximum, i.e., a probability mass equaling to the probability that the activity duration will exceed that maximum is placed at the maximum. The resulting mix distribution is used to generate activity durations in the simulation.

[6] Some of the explanatory variables in the model are endogenous. Potential estimation problems that may result are ignored at this stage of model development. Also note that activity durations in an observed data set are self-selected in the sense that only those activities that can be pursued within prism (and other) constraints can be recorded. This issue again is not addressed at this stage; application of more sophisticated estimation methods is a future task.

2.5. Validation

A validation analysis is conducted with the intent of evaluating how well the simulation system replicates observed activity and travel patterns. In the analysis expected values obtained from the PCATS simulation are compared against observed values for several indicators of activity-travel patterns. Expected values are obtained by performing 100 simulation runs for each sample individual and taking the average of the results over a total of 374 sample individuals whose activity records are complete. Table 1 summarizes the results.

Table 1
Results of the Validation Study

	Predicted		Observed			
	Mean	S.D.	Mean	S.D.	t	R^2
Total travel time	116.3	70.7	127.9	87.1	-2.00	0.622
In-home flexible activity duration	314.5	152.9	288.7	191.0	2.04	0.673
Out-of-home flexible activity duration	28.4	72.3	39.6	75.6	-2.07	0.329
Number of non-work destinations	0.071	0.61	0.31	0.58	-5.42	0.169
Number of non-work trip chains	0.059	0.28	0.013	0.11	2.86	-0.027
Number of trips	2.89	1.56	3.38	1.79	-4.00	0.576

S.D.: standard deviation across sample individuals
t: t-statistics associated with the difference between the predicted and observed values (not based on the standard deviations associated with “predicted” values)
R^2: Pearson correlation coefficient between predicted and observed values

Table 1 indicates that total travel time, in-home flexible activity duration, and number of trips are relatively well represented by the simulation. The t-statistics indicate, however, that predicted values and observed values are significantly different for all indicators (at $\alpha = 0.05$). In particular, number of non-work destinations and number of non-work trip chains have very small correlation coefficients. These discrepancies between the observation and prediction point to possible deficiencies in the model components, especially the activity type choice models. The results, nevertheless, demonstrate that the simulation system can replicate the observation reasonably well, at least with respect to total travel time, in-home flexible activity duration, and number of trips.

3. SCENARIO ANALYSIS

PCATS is applied in this section to assess how changes in the travel environment may affect an individual’s activity and travel. To this end, a sample individual’s activity and travel after the completion of work activities, are simulated using PCATS for the scenarios shown in Table 2. The sample individual has the following profiles: An employed male of 54 years old; a household income in the 1,500,000 to 2,000,000 yen range; has held a driver’s license for 30 years; one vehicle available to the household; commutes to CBD Osaka; lives in Kaizuka City which is approximately 30 km to the south from Osaka along the Osaka Bay and has good freeway access to the CBD.

The individual is assumed to be at the work location when work ends (which is assumed to represent the ending point of a blocked period), and the next blocked period is assumed to begin at midnight. It is thus assumed in the simulation that the entire evening period, after work till midnight, is an uncommitted block of time. Simulation is repeated 100 times for each scenario.

Table 2
Scenarios Used in the Simulation Analysis

Scenario	Description
Base case	Work ends at 5:00 PM. A car is used to commute.
Scenario 1	Work ends at 6:00 PM. A car is used to commute.
Scenario 2	Work ends at 5:00 PM. Public transit is used to commute.
Scenario 3	Work ends at 5:00 PM. Car commute takes extra 30 min.

The results of the simulation runs are summarized in Table 3. Since static travel time is used in the simulation, there is no random element in travel time (and therefore in in-home time) for the first travel pattern, "W-H," where the individual returns home immediately after work and engages in no out-of-home activity. In the base case, out-of-home activities are engaged in 16 of the 100 runs (16%). The mean out-of-home activity duration is 109 min. for the W-O-H pattern where out-of-home activities are engaged during the commute to home, while the mean duration is much shorter 52 min. in the W-H-O-H pattern where activities are engaged in separate home-based trip chains.

The frequency of the simple W-H pattern increases to 91, 89 and 90, respectively, in the three scenarios. Quite notable in Scenario 1, where work ending time is moved to 6:00 PM, is the substantial reduction in out-of-home activity duration and the slight reduction in travel time associated with the W-O-H pattern. In-home activity time does not show very much change. The shortening of the after-work open period caused by the change in work ending time has prompted the individual to engage in out-of-home activities less frequently. When the W-O-H pattern is engaged, the activity location is closer and the activity duration is much shorter, presumably to accommodate the tighter time constraints. These tendencies are not found for the W-H-O-H pattern, however. Yet, it is cautioned that the frequency of out-of-home activity engagement is small in the simulation results and the statistics presented under the W-O-H and W-H-O-H patterns contain large variations.

Similar reductions in out-of-home activity engagement can be found for Scenarios 2 and 3. The mean travel times associated with pattern W-O-H exhibit increases of less than 15 min. from the base case, while the activity times decrease by 15 to 20 min. Much larger changes are associated with the W-H-O-H pattern. This, however, is at least in part due to the small sample size.

Although the model system is still in its early stage of development and the analysis performed here is not extensive, this scenario analysis has demonstrated that PCATS facilitates the analysis of time-oriented policies such as changes in work schedules while explicitly considering time-space constraints in the analysis. PCATS also represents the repercussions of a change in the travel environment, including induced (or suppressed) travel and changes in activity location and duration.

Table 3
Results of Scenario Simulation with a Sample Individual

		After-work Travel Pattern[1]			
		W-H	W-O-H	W-H-O-H	Other
Base case	Frequency	84	8	7	1
	Travel time[2]	51	122	160	
	In-home time[2]	369	188	208	
	Out-of-home time[2]	0	109	52	
Scenario 1	Frequency	91	5	4	0
	Travel time	51	114	184	
	In-home time	309	177	115	
	Out-of-home time	0	69	62	
Scenario 2	Frequency	89	6	5	0
	Travel time	79	135	180	
	In-home time	341	190	155	
	Out-of-home time	0	94	85	
Scenario 3	Frequency	96	6	2	2
	Travel time	81	136	214	
	In-home time	339	195	178	
	Out-of-home time	0	89	29	

[1] W-H: work → home. W-O-H: work → other → home. W-H-O-H: work → home → other → home
[2] In minutes. Out-of-home time excludes travel time.

4. PCATS SUMMARY

PCATS is still in its early stage of development; it would be more appropriate to say it is an initial prototype. For example, the destination-mode choice model is not differentiated by trip purpose; the model system does not yet have the capability to endogenously generate fixed activities. There are many areas where development, extension and refinement are needed. Nevertheless it can be concluded that the study has demonstrated that activity-travel behavior in time-space prisms can be simulated reasonably well and that travelers' responses to changes in travel time or work schedules can be examined using the micro-simulation model system. The PCATS model system is readily applicable to other types of scenarios, such as changes in store hours or extended operating hours of public transit, which are difficult to address with the conventional trip-based models which do not incorporate the time dimension and disregard time-space constraints.

A future task, in addition to the above-mentioned development, extension and refinement of the model components, is to incorporate into PCATS the behavioral mechanism for activity engagement. The "utility-maximizing," nested-logit model of activity type choice in PCATS captures the salient tendencies associated with activity type choice; it, however, hardly captures the reason for activity engagement. The activity-type choice model as it is developed now, captures cross-sectional variations in activity engagement that are due to differences in personal and household attributes. It also represents the effects of the time of day and time availability on activity choice. The model thus emphasizes the effects of time constraints on activity choice. But it does not describe what motivates activity engagement, nor does it embody a behavioral mechanism of activity engagement. Effort is currently ongoing to introduce into PCATS the notion of time allocation to various activities, thus capturing the individual activity-travel scheduling effort as a resource allocation problem under prism constraints.

5. OVERVIEW OF AMOS[7]

AMOS is a "change model" which predicts changes in travel behavior that will follow a change in the travel environment. Its development has been motivated by the recognition that the traditional, trip-based, four-step procedures are incapable of addressing TDM and other policy measures that are now the primary focus of urban transportation planning. An AMOS prototype has been developed and implemented in the Washington, D.C., metropolitan area with the intent of predicting traveler response to selected TDM measures. The TDM measures considered for evaluation include: parking surcharge; bicycle/pedestrian facility improvements; parking pricing with employer-paid voucher; congestion pricing; and the combination of the first and second measures, and the combination of the third and fourth measures. AMOS comprises five main components and a reporting routine (see Figure 2). More detailed discussions can be found in RDC (1995) and Pendyala et al. (1996).

5.1. Baseline Activity-Travel Pattern Analyzer

The Baseline Activity-Travel Pattern Analyzer is summarized in Figure 3. It inspects daily travel diary data and determines whether the diary data under consideration are complete, with all trips and pertinent information intact. It also checks whether the sample trip maker and/or the travel pattern fall in the categories intended for analysis. Another major function the Analyzer performs is to develop indicators of travel pattern characteristics (e.g., there is a stop during the commute trip) that feed into the Response Option Generator. Trip diary data used are those typically available from metropolitan planning organizations (MPO's).

5.2. Response Option Generator

The Response Option Generator (Figure 4) is a key stochastic element of AMOS. The input to the Generator consists of: household and person attributes, network and land use characteristics, TDM attributes, and the indicators of the baseline activity-travel pattern characteristics prepared by the Analyzer. Given these, the Generator simulates how the sample individual responds to the TDM measure.

The central component of the Generator is a neural network which computes the probability that each possible response option will be adopted by the individual based on the input

[7] The description of the AMOS components in this section draws from Kitamura et al. (1995b).

variables.[8] The use of a neural network draws from the connectionism, a branch of cognitive science. Connectionists postulate that humans process information by breaking it down into smaller elements that are inter-connected with different levels of intensity. In other words, human thinking is a process of connecting one informational element (e.g., a concept) to another. This idea can be depicted by a neural network, which can be "trained" to best replicate observed connection patterns between input (in this case TDM attributes and other variables) and output (response options).

Generating a response option alone does not automatically produce a complete and feasible new activity-travel pattern. Quite often the primary change implied by the response option triggers secondary and tertiary changes. For example, a solo-driving commuter who stops at a grocery store on the way home from work, may choose to switch to public transit because of congestion pricing. To be able to do this, however, the commuter may also choose to make a home-based trip chain to a nearby grocery store by auto after returning home by bus. The next module performs such adjustments.

5.3. Activity-Travel Pattern Modifier

The Activity-Travel Pattern Modifier (Figure 5) examines the baseline pattern and, if the response option necessitates it, performs: (i) activity re-sequencing, (ii) activity re-linking, (iii) mode and destination assignment, and (iv) trip timing adjustment. Such adjustments are needed primarily when a travel mode change or a departure time change implied by the response option makes the baseline pattern infeasible or impractical. The modifier then examines the feasibility of the resulting modified activity-travel pattern using a rule base.

Activity re-sequencing refers to the re-arrangement of the order in which out-of-home stops are made. Re-linking, on the other hand, refers to the re-combining of out-of-home stops into trip chains. For example, consider a sequence of three out-of-home activities, A, B and W, where W is work. Suppose these three are pursued as A-W-B. This may be re-sequenced as W-A-B. Letting H be the home base, these activities may be linked as: H-W-A-B-H or H-W-H-A-B-H. In the former case, activities A and B are pursued on the way home from work; in the latter they are pursued in a separate home-based trip chain.

While the response option from the generator may dictate which mode is to be taken for some trips, there may be some degrees of freedom associated with other trips. In the latter case the modifier simulates mode choice for the set of trips whose modes are not fixed. Likewise, new destinations may be chosen for certain types of activities when activities are re-sequenced or re-linked, and the destination locations in the baseline pattern are no longer suitable.

The timing of trips is determined while using the work starting and ending times as "pegs" (Cullen, 1972). For example, the starting time of a home-to-work commute trip by a new mode will be determined such that the commuter will arrive at the workplace at or earlier than

[8] The response options were originally obtained during the computer-aided telephone interview (CATI) survey described in Section 6.1. They include: do nothing differently, change departure time to work, switch to transit, switch to car/vanpool, switch to bicycle, switch to walk, work at home, and others. Theoretically they may include the option, "switch to drive alone," which is not included in the prototype because no respondent volunteered this option.

the time observed in the baseline pattern. The duration of each out-of-home activity is fixed in this initial prototype.

After a modified activity-travel pattern is generated, the Modifier checks if it is feasible. Used in this check is a rule base, which contains several groups of rules that govern and constrain travel. For example shopping cannot be pursued outside the store hours. In fact this rule base is constantly referred to in the above process of modifying the baseline activity-travel pattern and producing an alternative.

5.4. Evaluation Routine

The Evaluation Routine (Figure 5) assigns a utility measure to the modified activity-travel pattern using time-use utility functions (see Kitamura et al., 1995a). The attractiveness of the modified pattern is determined by the utility produced by allocating time to, and engaging in, the in-home and out-of-home activities contained in the pattern. The utility functions are being developed using the time-use data obtained from the survey conducted as part of the study. The effort includes the generalization of the utility functions to include non-time elements such as mode attributes and monetary expenses, and sequencing and timing of activities. Using the time utility concept, AMOS evaluates TDM measures while considering their impacts on the entire daily activity, not just on the commute trips which these measures often target.

5.5. Acceptance Routine

The Acceptance (Search Termination) Routine (also Figure 6) evaluates the set of time-utilities associated with the activity-travel patterns so far generated, and determines whether the search should continue or one of the patterns so far generated should be adopted. The routine is based on the assumption that the individual forms a subjective distribution of utilities associated with alternative patterns; assesses the likelihood of obtaining a better activity-travel pattern; and terminates the search when the cost of search exceeds the expected gain of searching further. It is assumed that the individual can determine which of the alternatives so far evaluated has the largest utility and will choose that alternative. Experiments are being designed to validate this theoretical search termination model and to estimate the parameters.

5.6. Statistics Accumulator and Reporting Module

The Statistics Accumulator performs bookkeeping functions and produces two files. One is a temporary file and contains detailed information about the alternative activity-travel patterns generated for a sample individual in the simulation. This file supports the search process described above. The other file is a permanent file which contains the attributes of the pattern adopted by each sample individual. This file is later accessed by the Reporting Module to produce desired statistics and forecasts such as region-wide VMT and mode shares.

6. AMOS PROTOTYPE RESULTS

Results of the AMOS prototype implementation in the Washington, D.C., metropolitan area are summarized in this section.[9] A small-scale telephone interview survey was conducted to obtain data to calibrate model components, especially to train the neural network in the Response Option Generator. The implementation effort adopts the traffic analysis zone (TAZ) system and zone-to-zone network travel time matrices by travel mode, maintained by the Metropolitan Washington Council of Governments (MWCOG), the MPO of the region. Network skim travel time data are available for: drive alone (SOV), ride-sharing (HOV), public transit with walk access, and public transit with auto access. Travel times by bicycle and walk are estimated by applying assumed speeds (6.5 mph and 2.5 mph, respectively) to the centroid-to-centroid distance. The implementation effort thus utilizes as much information as available from the MWCOG data base. Note that travel time data used are static; possible changes in network service levels due to TDM measures are not reflected in the current application.

6.1. AMOS Survey

A three-phase survey, using computer-aided telephone interview (CATI) techniques, was conducted to generate a data set to calibrate AMOS components. The survey, which targeted commuters, included a time-use section which collected data on both in-home and out-of-home activities as well as details of each trip made. Also in the survey was a set of customized stated-preference (or "stated adaptation") questions which asked respondents how they would respond to each of a set of TDM measures. The survey was conducted in November and December of 1994, and approximately 650 interviews were completed. Adult commuters who commuted at least three days a week were the target of the survey. For further information, see RDC (1995) and Pendyala et al. (1996).

6.2. TDM Measures Considered

In the stated-adjustment section of the survey, respondents were given a description of a TDM measure (see Table 4 for the measures included), then asked in an open-ended format "What would you do?" if the measure had been in fact implemented. Follow-on questions were asked to probe into details of the stated behavioral adjustment (e.g., how to drop off a child at the day-care when public transit is used to commute). Commute travel time and other pertinent parameters were customized such that the hypothetical scenario would closely represent each respondent's commute situation.

Table 4
TDM Measures Included in the AMOS Survey in the Washington, D.C. Metropolitan Area

TDM #1	**Parking Tax**. Incremental parking tax at work place at - $1 to $3 per day in suburbs[*]

[9] An early predecessor to this effort where an activity-based model system can be found in van der Hoorn (1983), whose model system was developed based on a weekly time-use data set.

	- $3 to $8 per day in D.C. and central areas
TDM #2	**Improved Bicycle/Pedestrian Facilities**. Well-marked and well-lighted bicycle paths and a secure place to park a bicycle wherever respondent went.
TDM #3	**"Synergy" Combination of TDM 1 and TDM 2**
TDM #4	**Parking Charge Combined with Employer-Supplied Commuter Voucher.** Employers provide employees with a commuter voucher while employees must pay for a parking surcharge. - $40 to $80 per month for both voucher and surcharge
TDM #5	**Congestion Pricing**. Area-wide implementation of congestion pricing, effective from 6:00 AM to 9:00 AM and from 4:00 PM to 7:00 PM. - $0.15 to $0.60 per mile - 10% to 30% travel time savings
TDM #6	**"Synergy" Combination of TDM 4 and TDM 5**

*Different parameter values are assigned to respondents randomly within the range shown.

6.3. Neural Network

Responses to the TDM section were used to train the neural network of the Response Option Generator. The trained network consists of 45 input nodes and 8 output nodes with two hidden layers. The input nodes may be grouped as those representing: personal and household attributes, work schedule characteristics, commute characteristics, trip chaining characteristics, mode characteristics, and TDM scenarios. The eight output nodes comprise: change departure time, use transit to work, ride-share to work, ride bicycle to work, walk to work, work at home, do nothing different, and other (long-term responses treated as doing nothing in short-term policy analysis). A statistical procedure was developed to convert the output of the neural network, which lies between 0 and 1 but is not a probabilistic measure, into the probability that each response option will be adopted. The set of probabilities thus obtained is used in the simulation. Note that these probabilities vary from individual to individual depending of the person and household attributes and travel characteristics.

6.4. Simulation Results

Following scenarios are considered in the implementation study:

- TDM #1, parking pricing: parking surcharge of $8.00 per day,
- TDM #4, parking pricing with employer-paid voucher: parking charge of $80 per month and a commuter voucher of $60,
- TDM #5, congestion pricing: congestion charge of $0.50 per mile, travel time reduction by 30%, and
- TDM #6, a synergy combination of TDM #4 and TDM #5: parking charge of $80 per month, commuter voucher of $60, and congestion charge of $0.50 per mile.

The number of sample households from the MWCOG data base that were made available to the study was unfortunately very small and the results presented here are subject to sampling errors.[10] It must be noted that this exercise has been made for illustrative purposes and the size of the sample used here, and some of the simplifying assumptions existent in the prototype, warrant neither generalization of the results obtained nor general assessment of the relative effectiveness of the TDM scenarios examined here.

A total of 20 simulation runs were performed for each TDM measure, and the average of the 20 runs are used in the analysis. In the rest of this section, the baseline case is first examined, then simulation results for TDM#1 and TDM#5 are discussed. For additional results, see RDC (1995).

6.4.1. Baseline

Table 5 presents the distribution of trip purposes (work vs. non-work), travel mode (auto-driver, auto-passenger, other), mean trip duration by mode, percent of hot starts, and average number of trips per person, for AM peak, PM peak and off-peak periods. Over 60% of the trips are work trips in the morning peak period (non-work trips include trips from work to home), and about three-quarters of the trips are made by auto. The large fraction of trips by "other" mode in the afternoon peak period represents walk trips made in this period by this sample of commuters. The average number of trips per person is 3.21 for this sample of commuters.

Table 5
Baseline Travel Characteristics

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	42.2%	64.0%	31.1%	36.6%
Non-Work	57.8%	36.0%	68.9%	63.4%
TRAVEL MODE				
Auto - Driver	54.0%	65.1%	54.7%	45.5%
Auto - Passenger	18.4%	10.5%	18.9%	23.6%
Other	27.6%	24.4%	26.4%	30.9%
TRIP DURATION (min.)				
Total	18.5	21.7	22.0	13.4
Auto-Driver	21.6	24.5	24.9	15.2
Auto-Passenger	17.0	16.4	21.4	14.2
Other	13.6	16.4	16.2	10.1
HOT STARTS (%)	37.7%	34.9%	35.9%	37.8%
PERCENT OF TRIPS	100%	27.3%	33.7%	39.0%
TRIPS PER PERSON	3.21			

6.4.2. Parking Pricing (TDM#1)

[10] in the future the spatial and temporal resolution of micro-simulation results can be refined by using more households, possibly synthetic households distributed over the study area; see Kitamura et al. (1997).

The most notable change with the parking surcharge of $8 a day is in modal split (Table 6). The fraction of auto driver trips decreased from 54.0% in the baseline case to 47.5%, and auto passenger trips from 18.4% to 16.4%. The fraction of "other" modes increased by 7.8% during AM peak, 6.3% in the PM peak and 4.4% during off-peak periods, respectively.

The overall average trip duration (in min.) shows only small changes between the two cases. Importantly, however, the mean "other" trip duration increased from 13.6 min. to 18.4 min, suggesting that long-distance commuters tended to remain auto commuters while shorter distance travelers adopted other options. The distribution of trips across morning peak, afternoon peak and off-peak shows only minor changes. The fraction of morning peak trips decreased slightly from 34.9% to 34.5%, while that of afternoon peak trips increased from 35.9% to 37.4%. The average number of trips per person increased slightly from 3.21 to 3.31. This reflects activity re-linking as a result of a commute mode change, which resulted in slightly more trips per person.

Table 6
AMOS Simulation Results: Parking Pricing (TDM #1)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	43.2%	63.2%	35.5%	35.4%
Non-Work	56.8%	36.8%	64.5%	64.6%
TRAVEL MODE				
Auto - Driver	47.5%	57.5%	48.6%	40.8%
Auto - Passenger	16.4%	10.3%	18.7%	23.9%
Other	36.1%	32.2%	32.7%	35.3%
TRIP DURATION (min.)				
Total	19.4	21.6	22.8	13.4
Auto-Driver	21.2	23.6	24.8	15.3
Auto-Passenger	16.5	16.4	21.4	14.2
Other	18.4	19.7	20.7	10.5
HOT STARTS (%)	37.4%	34.5%	37.4%	39.2%
PERCENT OF TRIPS	100%	26.9%	33.0%	40.1%
TRIPS PER PERSON	3.31			

6.4.3. Congestion Pricing (TDM#5)

The results with congestion pricing at a level of $0.50 per mile with 30% reduction in travel time, are summarized in Table 7. The fraction of auto trips, 50.2%, is higher with this TDM than with parking pricing (47.5%), but is lower than the baseline result (54.0%). Other than mode shares, the results of this TDM are very similar to those of TDM#1.

Table 7
AMOS Simulation Results: Congestion Pricing (TDM #5)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	43.0%	64.4%	35.6%	36.5%
Non-Work	57.0%	35.6%	64.4%	63.5%
TRAVEL MODE				
Auto - Driver	50.2%	56.3%	51.9%	39.7%
Auto - Passenger	17.0%	10.3%	18.3%	22.2%
Other	32.8%	33.4%	29.8%	38.1%
TRIP DURATION (min.)				
Total	19.0	23.0	22.6	13.5
Auto-Driver	21.4	23.5	24.5	16.1
Auto-Passenger	17.3	16.4	21.8	14.5
Other	16.2	24.2	19.9	10.2
HOT STARTS (%)	36.8%	34.5%	36.5%	34.9%
PERCENT OF TRIPS	100%	26.9%	32.2%	40.9%
TRIPS PER PERSON	3.30			

6.5. Discussion

The exercise reported here has shown that AMOS, an activity-based micro-simulation model system, is capable of producing travel forecasts by simulating daily travel patterns. It has also demonstrated that the TDM measures considered here do have certain impacts on travel demand. From model development viewpoints, results are very encouraging as they show that activity-based models can be implemented in a metropolitan region and can produce forecasts for policy analysis in a practical manner.

From transportation policy viewpoints, however, the results may seem less encouraging because the effects of the TDM scenarios examined here are relatively small, and because there are only a few discernible differences among the impacts of the respective TDM scenarios. These results may be simply due to the small sample used in the exercise. It is conceivable that the commuters in the sample had very limited alternative commute options and were able to respond within very narrow ranges to whatever TDM scenarios being implemented. Whether this observation can be generalized or not needs to be determined in the future by analyzing a larger sample of individuals.

Another possibility is that the Response Option Generator has not been fine-tuned enough to be able to detect possibly minute differences in commuters' responses to different TDM measures. In particular, the results suggest that a neural network be developed for each TDM measure separately (in the current prototype, the neural network is designed to be able to handle all the TDM scenarios examined here).

The invariance in simulation results across the TDM scenarios may also be due to the limitations of the prototype used for the analysis. Importantly, destination choice has not been implemented in the prototype. In addition, the simplistic evaluation and acceptance rules adopted in the prototype may have resulted in premature search termination for each commuter, possibly leading to the acceptance of the baseline patterns with a higher probability than it should receive.

7. AMOS SUMMARY

This exercise has demonstrated that a micro-simulation model system of daily travel behavior, which adheres to the principles of the activity-based approach, is not only feasible but also will be a practical tool for policy analysis. The implementation of the AMOS prototype in the Washington, D.C., metropolitan area utilizes the data base maintained by the MPO of the area. The medium scale survey (about 650 respondents) used in this study can be modified to entertain a wide range of TDM measures, making AMOS a flexible and realistic tool for transportation policy analysis.

AMOS is a model of adaptation. It replicates the cognitive process of searching for the best activity-travel alternative given a change in the travel environment. The cognitive process is formulated as: the individual selects a principal change in the activity-travel pattern in response to the change in the travel environment, then makes adjustments to the activity-travel pattern while considering various constraints and rules. The new pattern is then evaluated and its superiority relative to the other patterns so far examined, is assessed. This process is repeated until a satisfactory pattern is obtained. This process may represent the individual's trial-and-error search effort which may take place over a period of several weeks, or it may be thought of as a replication of purely mental exercises of devising suitable ways of adapting to the change in the travel environment. In any event, underlying the development of AMOS is the intent of replicating how the individual "thinks" and decides what to do and how to travel.

Efforts are ongoing currently on several fronts to extend the scope of AMOS by incorporating: vehicle transaction and utilization behavior, vehicle allocation, and synthetic generation of households and their activity-travel patterns.[11] Planned future research activities include the development and incorporation of models for: search termination, activity engagement, time allocation, inter-person interaction, and multi-day behavior. Incorporating of realistic search strategies is another area for future effort.

8. CONCLUSION

Two computational process model systems of activity-travel behavior, PCATS and AMOS, are presented in this paper. The two model systems are motivated by different objectives, are built with different emphases, and are suited for different analytical purposes. PCATS, which explicitly incorporates Hägerstrand's time-space prisms, is suited for the analysis of factors that affect time-space constraints such as store opening hours, work schedules, and public transit operating hours. PCATS also offers a coherent analytical framework for examining induced or suppressed demand and addressing the effects of added capacity or mounting traffic congestion on travel demand. AMOS, on the other hand, is a model system of behavioral adjustment. It is a policy tool that predicts changes in demand by simulating how individuals respond to changes in their travel environments. As such AMOS is best suited for the evaluation of the effectiveness of policy options such as TDM measures. The scenario analyses presented in this paper using prototypes of these two model systems, have

[11] See Kitamura et al. (1996b).

demonstrated that activity-based model systems are practical tools for policy analysis and warranted the development of full-scale model systems.

ACKNOWLEDGMENTS

Funding for the development of PCATS has been provided by the Ministry of Education of Japan. The development and implementation of AMOS has been funded by the U.S. Environmental Protection Agency (EPA), Federal Highway Administration (FHWA), and Metropolitan Washington Council of Governments (MWCOG). The authors are grateful to the AMOS development team, which has included Cynthia Chen, Seyoung Kim, Keith Lawton, Clarisse Lula, Eric Pas, Ram Pendyala, Purasuna Reddy, and David Reinke.

REFERENCES

Axhausen, K.W. and T. Gärling (1992) Activity-based approaches to travel analysis: Conceptual frameworks, models, and research problems. *Transport Reviews*, **12**(4), 323-341.

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

Cullen, I.G. (1972) Space, time, and the disruption of behavior in cities. *Environment and Planning*, **4**, 459-70.

Damm, D. (1983) Theory and empirical results: a comparison of recent activity-based research. In S. Carpenter and P.M. Jones (eds.) *Recent Advances in Travel Demand*, Gower Publishing, Aldershot.

Ettema, D. (1996) Activity-Based Travel Demand Modeling. Unpublished Ph.D. dissertation, Faculteit Bouwkunde, Technische Universiteit Eindhoven, 297 p.

Gärling, T., M.-P. Kwan and R.G. Golledge (1994) Computational-process modelling of household activity scheduling. *Transportation Research B*, **28B**(5), 355-364.

Hoorn, T. van der (1983) Experiments with an activity-based travel model. *Transportation*, **12**, 61-77.

Jones, P.M., M.C. Dix, M.I. Clarke and I.G. Heggie (1983) *Understanding Travel Behaviour*. Gower Publishing, Aldershot.

Jones, P., F. Koppelman and J.P. Orfueil (1990) Activity analysis: State-of-the-art and future directions. In P. Jones (ed.) *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, Gower Publishing, Aldershot.

Kitamura, R. (1988) An evaluation of activity-based travel analysis. *Transportation*, **15**, 9-34.

Kitamura, R., C. Chen and R.M. Pendyala (1997) Generation of synthetic daily activity-travel patterns. Presented at the 76th Annual Meeting of the Transportation Research Board, Washington, D.C., January.

Kitamura, R., S. Fujii and Y. Otsuka (1996) An analysis of induced travel demand using a production model system of daily activity and travel which incorporates time-space constraints. Presented at the Fifth World Congress of the Regional Science Association International, Tokyo, May.

Kitamura, R., T. van der Hoorn and F. van Wijk (1995) A comparative analysis of daily time use and the development of an activity-based traveler benefit measure. Presented at the Conference on Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, May.

Kitamura, R., C.V. Lula and E.I. Pas (1993) AMOS: An activity-based, flexible and truly behavioral tool for evaluation of TDM measures. *Proceedings of the 21st Summer Annual Meeting: Transportation Planning Methods*, PTRC Education and Research Services, Ltd., London, pp. 283-294.

Kitamura, R., E.I. Pas, C.V. Lula, T.K. Lawton and P.E. Benson (1996) The sequenced activity mobility simulator (SAMS): An integrated approach to modeling transportation, land use and air quality. *Transportation* (forthcoming).

Kitamura, R., R.M. Pendyala, E.I. Pas and P. Reddy (1995) Application of AMOS, an Activity-Based TCM Evaluation Tool, to the Washington, D.C., Metropolitan Area. *23rd European Transport Forum: Proceedings of Seminar E Transportation Planning Methods*, PTRC Education and Research Services, Ltd., London, pp. 177-190.

Kurani, K.S. and R. Kitamura (1996) Recent Developments and the Prospects for Modeling Household Activity Schedules. A report prepared for the Los Alamos National Laboratory, Institute of Transportation Studies, University of California, Davis, California.

Newell, A. and H.A. Simon (1972) *Human Problem Solving*. Engelwood Cliffs, New Jersey: Prentice-Hall.

Otsuka, Y. (1996) Development of a Simulation Model System of Activity and Travel Which Represents the Individual's Decision Process. Unpublished M.S. thesis, Department of Applied Systems Engineering, Kyoto University, Kyoto (in Japanese).

Pendyala, R.M., R. Kitamura and D.V.G. Prasuna Reddy (1996) A rule-based activity-travel scheduling algorithm integrating neural networks of behavioral adaptation. Proceedings of the Conference on Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, May 1995 (forthcoming).

RDC, Inc. (1995) Activity-Based Modeling System for Travel Demand Forecasting. A Travel Model Improvement Program (TMIP) final report prepared for Metropolitan Washington Council of Governments, San Francisco, CA, August.

Tasker, M.P. and K.W. Axhausen (1994) DynaMIT: A Travel Behaviour Simulation Using Satisficing Search Methods. University of London Centre of Transport Studies, Imperial College of Science, Technology and Medicine, London.

Simon, H.A. (1990) Invariants in human behavior. *Annual Review of Psychology,* **41**(1), 1-19.

Figure Titles

Figure 1. PCATS Activity Type Choice Model for Simulation of Activity and Travel in the Open Period

Figure 2. Outline of Activity-Mobility Simulator (AMOS)

Figure 3. AMOS Baseline Activity-Travel Analyzer

Figure 4. AMOS Response Option Generator

Figure 5. AMOS Activity-Travel Pattern Modifier

Figure 6. AMOS Evaluation and Acceptance Routines