Generation of Synthetic Daily Activity-Travel Patterns

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Microsimulation approaches to travel demand forecasting are gaining increased attention because of their ability to replicate the multitude of factors underlying individual travel behavior. The implementation of microsimulation approaches usually entails the generation of synthetic households and their associated activity-travel patterns to achieve forecasts with desired levels of accuracy. A sequential approach to generating synthetic daily individual activity-travel patterns was developed. The sequential approach decomposes the entire daily activity-travel pattern into various components, namely, activity type, activity duration, activity location, work location, and mode choice and transition. The sequential modeling approach offers practicality, provides a sound behavioral basis, and accurately represents an individual's activity-travel patterns. In the proposed system each component may be estimated as a multinomial logit model. Models are specified to reflect potential associations between individual activity-travel choices and such factors as time of day, socioeconomic characteristics, and history dependence. As an example results for activity type choice models estimated and validated with the 1990 Southern California Association of Governments travel diary data set are provided. The validation results indicate that the predicted pattern of activity choices conforms with observed choices by time of day. Thus, realistic daily activity-travel patterns, which are requisites for microsimulation approaches, can be generated for synthetic households in a practical manner.

Microsimulation of the behavior of a household or an individual is drawing attention as a new approach to travel demand forecasting (1). Microsimulation can replicate the behavior of complex systems or processes and is therefore suited for the representation of travel behavior, which is a complex behavior. The factors that make travel behavior complex include the multitude of contributing factors and decision rules involved, constraints that govern the behavior, interpersonal interactions, multiple planning horizons, and complexity of activity-travel decision making as a scheduling problem (2). Microsimulation is an effective approach to such a complex phenomenon that facilitates its practical, yet realistic, representation.

Achieving desired levels of accuracy in the outcome of travel demand forecasts produced by microsimulation of household behavior may require a large sample of households. This may happen when high levels of spatial or temporal resolution of the outcome are required, sample households do not have a desirable geographical distribution, demand by small population segments is desired, or a high level of accuracy is desired. In such instances the number of households available in the data set at hand may not be sufficiently large. As a result the generation of synthetic households may be required. When the microsimulation expects daily travel patterns of

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household members as input data, the generation of synthetic daily travel patterns will be required.

An approach to the problem of synthetic travel pattern generation is presented in this paper. The proposed synthetic travel pattern generator has a sequential structure and can be decomposed into components to which certain aspects of observed activity-travel behavior correspond, thus establishing a link between mathematical models and observational data. The model components are each relatively simple and are estimated by commonly adopted estimation methods and with existing data sets.

PROBLEM DESCRIPTION

Consider a household member, i, whose daily activity-travel pattern can be characterized as

$$(\mathbf{X}_i, \mathbf{T}_i, \mathbf{L}_i)$$
$$= (X_{i0}, X_{i1}, \ldots, X_{in}; T_{i0}, T_{i1}, \ldots, T_{in}; L_{i0}, L_{i1}, \ldots, L_{in}) \qquad (1)$$

where

X_{ij} = type of jth activity pursued by individual i,

T_{ij} = duration of jth activity pursued by individual i,

L_{ij} = location of jth activity pursued by individual i (if activity is travel, then L_{ij} refers to destination of trip j; in this case $L_{ij} = L_{ij+1}$),

n = number of activities involved in individual i's daily activity-travel pattern, and

(X_{i0}, T_{i0}, L_{i0}) = initial condition.

Note that travel is included here as one of the activity types. For simplicity, travel mode, which may be stored in another vector, say $\mathbf{M}_i$, is not included in the discussion here. The mode choice component is discussed in a subsequent section of this paper.

The development of a synthetic daily activity-travel pattern implies the generation of vectors $\mathbf{X}_i$, $\mathbf{T}_i$, and $\mathbf{L}_i$ given the following:

- Attributes of individual i,
- Attributes of the household to which i belongs,
- Residence and work location of i,
- Demographic and socioeconomic characteristics of the region,
- Land use characteristics of the region, and
- Transportation network and travel time characteristics of the region.

Because it is most likely that synthetic activity-travel patterns will be generated for synthetic individuals and households, the first three items will make up synthetic data. Generating synthetic individuals and households, however, is beyond the scope of this paper [a previous report discusses the generation of synthetic households (3)]. It

is assumed here that all personal and household attributes, as well as work location, are known for i. These last three items will consist of projected values in cases in which synthetic activity-travel patterns are generated for forecasting.

ACCUMULATED KNOWLEDGE

The following discussions offer a brief summary of what is known about n, which is also a variable to be determined, and each of the three vectors, $\mathbf{X}_i$, $\mathbf{T}_i$, and $\mathbf{L}_i$. It is possible that additional information on time use is available from the literature. This literature is not well known in the transportation field and needs to be explored further in the future.

Number of Activities Per Day: n

The total number of activity episodes captured in time use surveys tends to be 20 to 25 per person per day, including trips. In the transportation field, the average number of trips is between 3 to 5 per person per day. It is known that the number of trips captured varies greatly depending on the survey methodology. It is well established that total trip generation is associated with the demographic and socioeconomic attributes of the traveler.

Activity Type: X_i

There are certain regularities in the sequence with which individuals engage in different types of activities. For example, one may anticipate that the sequence of activities performed before leaving home for work or after coming back home from work is fairly uniform across individuals. The literature in time use analysis needs to be explored to determine tendencies for activity sequences involving both in-home and out-of-home activities (4).

Kitamura (5) examined the sequence of trip purposes by using standard trip diary data from Detroit, Michigan. The trip purpose was used to identify the primary out-of-home activity type at each destination location. The analysis examined how out-of-home activities were sequenced in a home-based trip chain, that is, the home-to-home series of trips that involve one or more stops. The results indicated that activities of a more mandatory nature tend to be pursued first in a trip chain. The sequencing tendencies indicated the following hierarchy:

- Work and school, work related;
- Chauffeuring;
- Personal business (e.g., banking, dental, and medical);
- Shopping; and
- Social and recreational.

The presence of the same sequencing hierarchy was later found for activities throughout the day (6,7). Another important tendency is that activities pursued in the same trip chain tend to be similar (5).

Activity Duration: T_i

Several studies have investigated the duration of activity engagement. In a semi-Markov process model of trip chaining, Lerman (8) used gamma distributions to represent the duration of sojourns at destination locations. Survival models have recently been applied to the time dimension in activity-travel patterns (9–11). These studies are typically based on the simplifying assumption that the durations of successive activities are independent.

Activity duration has been examined from the viewpoint of resource allocation. Kitamura et al. (12) presented a theoretical model in which the duration of an activity episode was analytically derived while assuming that the total daily activity pattern is optimized and that each activity episode has a logarithmic utility function. The model was estimated with a time use data set from the United States. Although the model is based on the assumption that daily time use is optimized as a whole, the resulting model applies to individual activity episodes. Golob and McNally (13) examined the allocation of time to different activity types using a structural equations model system. This approach facilitates the inference of causal relationships among activities of different types.

Critical in the analysis of activity duration is the correlation across the duration of respective activity episodes. Because the total amount of time available is fixed at 24 hr a day, negative associations can be expected. In addition, the duration of each episode is also a function of n, the total number of episodes. The interrelationships among the durations of different types of activities and the number of activities, n, merit further exploration.

Activity Location: L_i

Nonhome activity locations traditionally have been estimated by using the gravity model of spatial interaction. The multinomial logit model of destination choice can be viewed as a special case of the gravity model family. In principle, these models depict that, all other things being equal, more intense interaction exists between a pair of locations that are closer to each other and that the intensity of the interaction is positively related to the attraction level of the destination and the number of trips initiated at the origin.

One important issue is the characterization of location or destination choice for non-home-based trips, that is, trips whose origin and destination are both nonhome. For home-based destination choice underlying a simple trip chain involving only one stop (i.e., home-activity-home), the only spatial element to be considered is the separation between the destination and the home base. This does not hold true in the case of non-home-based choice. For example, consider the choice of a shopping location on the way home from work; in this case both the home location and the deviation from the regular commute route would be important considerations. Kitamura and Kermanshah (7) constructed a non-home-based destination choice model that included both the usual origin-to-destination travel time, t_{ij}, and the destination-to-home travel time, t_{ih}, in a multinomial logit choice model. Their estimation results clearly indicated that t_{ij} and t_{ih} are equally important for non-home-based destination choice. This finding is readily applicable to the generation of synthetic activity-travel patterns.

Travel Mode: M_i

There are numerous studies on travel mode choice. Most studies, however, are seriously limited because they are trip based, that is, they analyze each trip separately in isolation from other trips. Consider the choice of commuting by car because a car is needed for work. Then this mode choice behavior cannot be explained by solely

examining the home-to-work commute trip and comparing the attributes of the travel modes available for that trip.

One of the critical requirements in synthetic pattern generation is observation of the constraints imposed on the transition between travel modes. For example, transition from public transit to driving alone is usually not possible unless the transition takes place at the home or work base where a private car is placed or at a special facility such as a park-and-ride lot. For a trip chain that originates and terminates at the home base, the sequence of travel modes tends to be governed by the boundary condition that the mode of the first trip from home is identical to that of the last trip to home. These regularities and tendencies serve as a set of constraints in the generation of activity-travel patterns.

MODELING CONSIDERATIONS

There are two broad classes of approaches to the generation of synthetic activity-travel patterns: sequential (incremental) approaches versus simultaneous (holistic) approaches. The former adopt rules to generate, one by one, the activity that will immediately follow, given the history of activity generation so far. The latter approaches, on the other hand, deploy behavioral paradigms that are each concerned with the entire daily activity-travel pattern.

One paradigm for the simultaneous approaches is that an individual with given attributes has a probability vector that depicts the likelihoods with which he or she will exhibit respective activity-travel patterns. A study by Pas (*14*) is readily applicable to the operationalization of this paradigm. Another paradigm is utility maximization, in which an individual chooses that activity-travel pattern, from among a set of all feasible patterns, that offers the maximum utility. Studies based on this assumption include those by Adler and Ben-Akiva (*15*), Recker et al. (*16*), and Recker (*17*). The two paradigms can be integrated to produce probabilities for alternative daily activity-travel patterns.

The simultaneous approaches have theoretical elegance. They can be expected to be more sensitive to parameters describing the travel environment than are sequential approaches. In addition, simultaneous approaches can better reflect an individual's travel planning effort. Despite the advantages offered by simultaneous modeling approaches, a sequential approach is proposed in this study. There are three major reasons:

- *Practicality.* One important advantage of sequential approaches is the ease of implementation that they offer. When viewed as an optimization problem, daily activity-travel behavior is very complex (*2*). Exact formulation of this behavior produces an overwhelmingly complex mathematical problem. The size of the problem at each step is much smaller in sequential approaches because a daily pattern is synthesized incrementally.

- *Behavioral basis.* Sequential approaches do not lack a behavioral basis. For example, when proposing the paradigm of satisficing, Simon (*18*) noted that a person is not capable of enumerating all possible alternatives or discerning minute differences among them. Furthermore, a person often will not have complete information associated with all alternatives. As such, even though certain travel choices may be considered simultaneously, it may be argued that people sequentially process "information elements" to reduce the size and dimensionality of the problem.

- *Contexts of synthetic activity-travel pattern generation.* Synthetic activity-travel patterns are usually generated to represent baseline travel characteristics of the population under prevailing

conditions. In this context, sequential model systems offer policy sensitivities that are consistent with the objectives of synthetic pattern generation.

The sequential approach adopted in this paper is based on the identity that, given n, the X-T-L triple can be expressed as

$$
\begin{aligned}
&\Pr[X_i, T_i, L_i] \\
&= \Pr[X_{i1}, X_{i2}, \ldots, X_{in}; T_{i1}, T_{i2}, \ldots, T_{in}; L_{i1}, L_{i2}, \ldots, L_{in}] \\
&= \Pr[X_{in}, T_{in}, L_{in} | X_{i1}, X_{i2}, \ldots, X_{i,n-1}; \\
&\quad T_{i1}, T_{i2}, \ldots, T_{i,n-1}; L_{i1}, L_{i2}, \ldots, L_{i,n-1}] \\
&\quad \times \Pr[X_{i,n-1}, T_{i,n-1}, L_{i,n-1} | X_{i1}, X_{i2}, \ldots, X_{i,n-2}; \\
&\quad T_{i1}, T_{i2}, \ldots, T_{i,n-2}; L_{i1}, L_{i2}, \ldots, L_{i,n-2}] \\
&\quad \times \ldots \times \Pr[X_{i1}, T_{i1}, L_{i1}]
\end{aligned}
\tag{2}
$$

Each probability on the right-hand side can be formulated as a model for activity type, location, and duration, given the past history of activity and travel. In adopting the sequential approach, the joint probability of an X-T-L triple needs to be decomposed into sequential elements. The following decompositions are possible:

$$
\begin{aligned}
&\Pr[X_{ij}, T_{ij}, L_{ij} | \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
&= \Pr[L_{ij} | X_{ij}, T_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
&\quad \cdot \Pr[T_{ij} | X_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \Pr[X_{ij} | \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
&= \Pr[T_{ij} | X_{ij}, L_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
&\quad \cdot \Pr[X_{ij} | L_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \Pr[L_{ij} | \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
&= \ldots
\end{aligned}
\tag{3}
$$

and so forth, where $\tilde{X}_{i,j-1}$ is equal to $(X_{i0}, X_{i1}, \ldots, X_{i,j-1})'$, and so forth.

Because all permutations of X_{ij}, T_{ij}, and L_{ij} lead to the same joint probability, the model's replication capability should not depend on which permutation is adopted. Therefore, that permutation that can be theoretically supported or that offers the most modeling flexibility and sensitivity can be selected.

EXPLORATION OF POTENTIAL ASSOCIATIONS

As noted previously, knowledge about the characteristics of activity-travel behavior has been accumulated. A few salient aspects of activity-travel behavior that merit inclusion in a synthetic generator are outlined in this section.

- *History dependence.* History dependence has been found to be prevalent in studies of activity type choice (*5,19*) and location choice (*20–24*). Although it is also likely that history dependence is prevalent for activity duration choice, the knowledge of the history dependence in activity duration appears to be extremely limited.

- *Time-of-day dependence.* Activity engagement is strongly dependent on the time of day. Tabulations of time use data (*25*) indicate surprising homogeneity in activity engagement across individuals. This is partly institutional (e.g., work and school) and partly physiological (e.g., meals and sleeping). The time-of-day dependence of activity engagement can be represented by formulating engagement probabilities as time-dependent functions (*6*).

- *Spatial and temporal constraints.* Different activities have different levels of constraints in terms of (*a*) engagement, (*b*) duration, (*c*) location, and (*d*) timing. Higher levels of engagement and duration constraints are typically associated with work and school (mandatory) activities. It may be assumed that more flexible activities are organized around these constrained activities. Some types of activities may have tight constraints when they are pursued with

prior commitment, for example, a medical appointment. In general, constraints associated with activity engagement vary significantly depending on institutional and situational factors (e.g., store hours), prior arrangement and commitment, as well as the type of activity. An issue in this effort is whether constraints associated with each activity should be explicitly considered and modeled or treated as random elements. Considering data availability, only the latter approach is feasible. However, constraints on regular events such as work and school merit explicit consideration.

• *Planned versus unplanned activities.* Some activities are routine, some are planned ahead, yet some are unplanned and are pursued in response to unanticipated events. It is desirable that the degree of planning be represented when synthesizing travel patterns because it allows for the analysis of transportation policy impacts on an individual's travel plans. In the context of synthetic pattern generation, however, representing the level of planning in activity engagement is of lesser importance, given that the constraints associated with activities are well understood. Also, data availability is an issue. On the basis of these considerations, the model system in this study does not explicitly incorporate the degree of planning.

• *Travel time budget.* History dependence in L_i as well as in T_i would arise if a traveler allocates a certain amount of time for traveling. This leads to the notion of travel time budgets (*26*). There have been disputes on whether individuals have a fixed time budget that is invariant across individuals. However, more recent results offer evidence that when the duration of a trip is reduced, then a portion of the time saved tends to be used to travel more (*13,27*).

• *Prism constraints.* The spatial expanse that is accessible to an individual for activity engagement is determined by the speed of movement and the amount of time available. Hagerstrand (*28*) defined this expanse in the time-space dimension as the time-space "prism." The prism contains all possible locations where activities can be engaged and defines the amount of time available for activities at each location within it. Kondo and Kitamura (*29*) adopted the prism concept in the analysis of trip chaining behavior. Beckmann et al. (*26*) used the concept to define accessibility measures. The prism concept is important because it defines the state space for the evolution of location choice.

• *Trade-off between activity duration and travel time.* The trade-off between the duration of activity and the time spent reaching the activity location is also important. One may choose to visit a nearby opportunity and spend more time on the activity there or visit a farther but better opportunity and spend less time there. This consideration is adopted by Kitamura et al. (*12*) in the formulation of time-utility functions. The model in this study accounts for this by making the probability of L_{ij} conditional on T_{ij}.

• *Modal continuity, permissible transitions, and time-of-day dependence.* Despite the voluminous studies on travel mode choice, little is known on history dependence and time-of-day dependence of travel mode choice. Modal continuity and modal transition have rarely been addressed in the literature [a rare example can be found in the report by Kondo (*23*)]. In general, the travel modes used by an individual in a series of trips tend to be governed by the constraints surrounding modal transitions. In addition, because both transit and highway levels of service vary along the time of day, it is likely that mode choice is time-of-day dependent.

• *Relationships among travel choices.* It is now widely recognized that various dimensions of travel behavior are related to one another. For example, activity type choice influences destination choice because a traveler would choose a destination that fulfills the specific activity need. Similarly, interrelationships exist between destination choice and mode choice, activity type choice and depar-

ture time choice, and departure time choice and activity duration. The sequential model system developed in this study explicitly incorporates interdependencies among travel choice dimensions in synthesizing activity-travel patterns.

MODEL FORMULATION

For X_{ij} that is not travel, the following decomposition of the *X-T-L* triple may be adopted:

$$
\begin{aligned}
\Pr[X_{ij}, T_{ij}, L_{ij} | \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
= \Pr[L_{ij} | X_{ij}, T_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
\cdot \Pr[T_{ij} | X_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
\cdot \Pr[X_{ij} | \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}]
\end{aligned}
\tag{4}
$$

In this formulation an activity type is selected first; given the type, its duration is determined; and finally, a location is chosen given the type and duration. Each of these decision elements is assumed to be dependent on the past history of behavior. This formulation is based on the view that activity engagement is the most fundamental decision that drives duration and location choice. Although this may not hold true under all conditions, it may be regarded as a typical activity engagement decision process.

When X_{ij} is travel, the following decomposition would be more appropriate:

$$
\begin{aligned}
\Pr[X_{ij}, T_{ij}, L_{ij} | \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
= \Pr[T_{ij} | X_{ij}, L_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
\cdot \Pr[L_{ij} | X_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}] \\
\cdot \Pr[X_{ij} | \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}]
\end{aligned}
\tag{5}
$$

Namely, the destination, L_{ij}, is determined before travel time, T_{ij}. This reflects the view that travel time cannot be determined before destination and mode are determined.

Overview of Synthetic Travel Pattern Generator

The components of the synthetic travel pattern generator are as follows:

- Activity-type choice models
  - Home-based and non-home-based
  - Workers and nonworkers
- Activity duration models
  - Workers and nonworkers
  - By activity type
- Activity location choice models
  - Home-based versus non-home-based
  - Workers and nonworkers
  - By activity type
- Mode choice and mode transition models
  - Home-based and non-home-based
- Initial departure timing models
  - Workers and nonworkers
- Initial location models
  - Workers and nonworkers

where "worker" refers to an individual who is employed, either full-time or part-time, or a student. It is possible for a part-time worker's

daily activity-travel pattern to not include a commute trip. At this stage model components have been developed for weekdays only. The activity types used in the models are work, work-related, school, return to work, social and recreation, shopping, personal business, eat out, home (transient), and home (absorbing).

Activity-Type Choice Models

Activity-type choice models are concerned with $Pr[X_{ij}|\tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}]$. These models probabilistically determine the next activity type to be engaged. Two types of models, home-based models and non-home-based models, are developed. The former is for an out-of-home activity that follows an in-home sojourn, whereas the latter is for an activity, whether in-home or out-of-home, that follows an out-of-home sojourn. Although the latter includes "in-home activity" as an alternative in the choice set, the former excludes it. It is to be noted that the home-based versus non-home-based distinction does not refer to the location where the choice is made. Both types of models are developed for workers and non-workers separately. The history dependence of activity type transition is represented by formulating the probability of an activity type as a function of the series of activities so far engaged, $\tilde{X}_{i,j-1}$, the time that has been allocated to them, $\tilde{T}_{i,j-1}$, and the current location, $L_{i,j-1}$.

Activity Duration Models

Consider an activity type, a. Given X_{ij} is equal to a, T_{ij} will have a probability distribution function whose parameters are functions of $t, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, L_{i,j-1}$, and $\tilde{Z}_i$, as follows:

$$\Pr[T_{ij} \leq q | X_{ij}$$
$$= a, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{Z}_i]$$
$$= G_a(q: \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{Z}_i) \qquad q \geq 0, a = 1, 2, \ldots, k \qquad (6)$$

where t is the time of day when the $(j-1)$th activity ended and $\tilde{Z}_i$ is the vector of person attributes and other explanatory variables. G_a is a distribution function. Two sets of activity duration models are developed: one for workers and the other for nonworkers. The same activity classification scheme used in the activity-type choice models is adopted, and models are developed for all activity types except absorbing home (person returns home for the day).

Some distribution functions may be preferred over others for activity duration. For example, let an activity comprise n task elements, and let task completion times be identically and independently distributed with a negative exponential distribution for all task elements. Then the distribution of the duration of this activity is a type-n Erlang distribution. Other distributions, including negative exponential, Weibull, and log-normal distributions, have geneses that offer interpretations suitable for activity duration. The Weibull distribution is used in this modeling effort because of its goodness-of-fit and intuitively appealing interpretation in the context of activity duration modeling.

Activity Location Choice Models

The problem here is to determine the probability that the location of the jth activity is g, given the type and duration of the activity, the completion time of the $(j-1)$th activity, $t, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}$, and $\tilde{L}_{i,j-1}$. The models are formulated for all activity types, except in-home activity.

Home-Based Models

The home-based location choice models take on a form that is similar to conventional destination choice models:

$$\Pr[L_{ij} = g | h_i, X_{ij}, T_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{Z}_i, \tilde{A}, \tilde{S}]$$
$$= \Pr[L_{ij} = g | t, h_i, X_{ij} = a, T_{ij} = q, \tilde{Z}_i, \tilde{A}, \tilde{S}]$$
$$= H_a(g: t, h_i, q, \tilde{Z}_i, \tilde{A}, \tilde{S}) \qquad (7)$$

where

h_i = residence zone,
$\tilde{A}$ = vector of attractiveness measures of alternative locations, and
$\tilde{S}$ = matrix of origin-destination travel times.

Note the assumption that the location choice is conditionally independent of $\tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}$, and $\tilde{L}_{i,j-2}$, given t, h_i (which is equal to $L_{i,j-1}$), X_{ij} (which is equal to a), and T_{ij} (which is equal to q).

Non-Home-Based Models

As will be discussed later, a travel mode is assigned in the procedure before the selection of destination location for a trip whose origin is not the home base. Let M_{ij} be the mode of the trip made to the jth activity location. With the assumption that destination choice is conditionally independent of $\tilde{M}_{i,j-1}$, as well as $\tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}$, and $\tilde{L}_{i,j-2}$, given $t, h_i, L_{i,j-1}$ (which is equal to f), X_{ij} (which is equal to a), T_{ij} (which is equal to q), and M_{ij} (which is equal to r),

$$\Pr[L_{ij} = g | h_i, X_{ij}, T_{ij}, M_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{M}_{i,j-1}, \tilde{Z}_i, \tilde{A}, \tilde{S}]$$
$$= \Pr[L_{ij} = g | t, h_i, X_{ij} = a, T_{ij} = q, L_{i,j-1} = f, M_{i,j-1} = r, \tilde{Z}_i, \tilde{A}, \tilde{S}]$$
$$= Q_a(g: t, h_i, q, f, r, \tilde{Z}_i, \tilde{A}, \tilde{S}) \qquad (8)$$

Mode Choice and Mode Transition Models

A travel mode is assigned to each trip by using the following procedure: (a) the travel mode for the first trip in each home-based trip chain is determined (home-based models), and (b) a mode transition matrix is developed and applied to determine subsequent travel modes on a trip-by-trip basis (non-home-based models). The model system incorporates a dummy variable that indicates whether a private car is parked at the workplace, which makes the probability very high that a car will be used for a trip originating from the workplace. Models are developed for workers and nonworkers separately. Travel modes are grouped into automobile driver, automobile passenger, public transit, and bicycle and walk.

Home-Based Models

The home-based models incorporate accessibility indexes for the residence zone and, for workers, accessibility indexes for the work zone. Accessibility indexes by mode are defined as the "log-sum" variables of the utility functions of the destination choice models. Highway and transit travel times and distances to destination zones are also incorporated. Also included in the models are descriptors of the destination zone (e.g., percent retail) and the time of day when the trip starts. The models take on the following form:

$$\Pr[M_{ij} = r | h_i, X_{ij}, T_{ij}, L_{ij}, \tilde{X}_{i,j-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{M}_{i,j-1}, \tilde{Z}_i, \tilde{A}, \tilde{S}]$$
$$= \Pr[M_{ij} = r | t, h_i, X_{ij} = a, T_{ij} = q, L_{ij} = f, \tilde{H}_{i,j-1}, \tilde{Z}_i, \tilde{A}, \tilde{S}] \qquad (9)$$

where $\tilde{H}_{i,j-1}$ is defined as $\tilde{H}_{i,j-1} = (H_{i1,j-1}, H_{i2,j-1}, \ldots, H_{im,j-1})'$, with m being the number of modes and $H_{ir,j-1}$ being equal to 1 if $\tilde{H}_{i,j-1}$ contains mode r (for $r = 1,2, \ldots, m$) and $H_{ir,j-1}$ being equal to 0 otherwise.

Non-Home-Based Models

The non-home-based models are transition models that determine the probability that a certain travel mode will be used for a trip given the mode of the previous trip. Additional explanatory variables include descriptors of the destination zone, car-packed-at-work dummy (for workers), and the time of day. The non-home-based mode choice models are trip-end models that are applied before destination location is determined. They can be summarized as follows:

$$\Pr[M_{ij} = r | h_i, X_{ij}, T_{ij}, \tilde{X}_{i,i-1}, \tilde{T}_{i,j-1}, \tilde{L}_{i,j-1}, \tilde{M}_{i,j-1}, \tilde{Z}_i, \tilde{A}, \tilde{S}]$$
$$= \Pr[M_{ij} = r | t, h_i, w_{i,i-1}, X_{ij} = a, T_{ij} = q, M_{i,j-1} = u,$$
$$\tilde{H}_{i,j-1}, \tilde{Z}_i, \tilde{A}, \tilde{S}] \tag{10}$$

where $w_{i,j-1}$ is the car-parked-at-work dummy. As noted earlier, non-home-based mode choice models are transition models and replicate modal continuity conditions in the data set.

Initial Departure Timing Models

Initial departure timing models may be viewed as the duration models for the first activity of the day starting at, say, 3:00 a.m., which is typically an in-home activity (most probably, sleeping). In this study models are estimated for workers and nonworkers separately and are applied in synthetic pattern generation to those sample individuals who are at home at 3:00 a.m.

Initial Activity Type and Location Models

Initial activity type and location models determine the type and zonal location of the first activity. As noted earlier, this is usually an in-home activity and the location is the residence zone. Data sets thus do not typically offer rich information (in terms of variation across individuals) for these models. As a result they tend to be simple frequency models without many explanatory variables.

Work Location Models

Work location models are the equivalent of home-based work trip distribution models. The probability that a worker commutes to a certain zone is formulated as a function of network automobile travel times, zonal attributes, and person and household attributes. The models are formulated as multinomial logit models.

SAMPLE ESTIMATION RESULTS

This section provides sample results of the estimation of activity type choice models and activity duration models for work activity for workers and social-recreation activity for workers and non-workers. For brevity, the presentation of results has been limited to two modules of the generator and two activity types. This section s intended to provide a representative indication of the perfor-

mance of the model for mandatory (work) and discretionary (social-recreation) activities and for workers and nonworkers, thus covering a variety of behavioral conditions. The 1991 travel diary set of the Southern California Association of Governments is used for model estimation and validation purposes. The data set provides a total of 136,640 trip records for 32,515 individuals. As such, it provides rich information with a sufficient sample size in each population segment considered in this effort. Sample estimation results for each of the two modules are summarized in the subsections that follow.

Activity Type Models

The data set was randomly divided into two subsets; one subset was used for estimation purposes and the other was used for validation purposes. Multinomial logit models of activity type choice were estimated by using standard maximum-likelihood methods. Estimation and validation results are presented in Tables 1 and 2, respectively.

Table 1 presents estimation results for six activity type choice models. They are home-based and non-home-based models for workers (return to work, social-recreation) and home-based and non-home-based models for nonworkers (social-recreation).

Models estimated for workers set work as the reference alternative (utility is set equal to 0), whereas models for nonworkers set shopping as the reference alternative. Explanatory variables include socioeconomic characteristics of the person, dummy variables of time of day, and lagged dependent variables of history dependence. Those time periods that are not represented in the model are used as reference periods.

The models indicate the time-of-day dependence of activity type choice. For example, in the home-based model for workers, the "return to work" activity peaks at about 11:30 a.m. to 1:00 p.m.; this may be explained by workers having lunch and then returning to work. Social-recreation activities peak between 7:30 and 9:30 p.m., as evidenced by the larger coefficients associated with dummy variables representing evening hours. During the early morning, coefficients for social recreation are less than those for work, indicating that the work activity peaks during that period.

Socioeconomic variables also play important roles in determining activity type choice. The work and social recreation activity models presented in this paper do not include socioeconomic variables because they were found to be statistically insignificant at the 0.05 level. However, other activity types including personal business, shopping, eating out, and school (not shown in this paper) were significantly influenced by socioeconomic characteristics.

History dependence is represented by a lagged dummy variable, which takes on a value of 1 if the activity is performed earlier in the day and 0 otherwise. History dependence effects are found to be statistically insignificant for the return to work but are found to be significant in explaining workers' social-recreation activity engagement. The coefficients have negative signs indicating that if a social-recreation activity was pursued previously in the day, then there is a reduced likelihood of repeating the activity. History dependence was also found to be significant for other activity types, notably shopping and personal business (not presented in this paper).

Table 2 presents validation results for the six models for which estimation results were presented in Table 1. The validation results are presented by time of day over a 24-hr period for return-to-work and social-recreation activities. For each time period the actual frequency of each activity type and the expected frequency (calculated

TABLE 1   Sample Estimation Results for Activity Type Choice Models

HB for Workers/Students		HB for Non-workers/Non-students		NHB for Workers/Students		NHB for Non-workers/non-students	
Return to Work		*Return to Work*		*Return to Work*		*Return to Work*	
Variables	Estimates	Not Applicable		Variables	Estimates	Not Applicable	
Constant	-0.32 (-1.2)			Constant	-1.56 (-2.4)		
D(3-6:30am)	-0.82 (-0.6)			D(7:30-8:30am)	1.05 (1.5)		
D(6:30-7:30am)	-2.01 (-1.7)			D(8:30-9:30am)	1.67 (2.4)		
D(7:30-8:30am)	-1.35 (-1.6)			D(9:30-10:30am)	2.94 (4.4)		
D(8:30-9:30am)	-0.88 (-1.2)			D(10:30am-12:30pm)	3.83 (5.9)		
D(9:30-11:30am)	0.87 (2.2)			D(12:30-2:30pm)	4.75 (7.3)		
D(11:30am-1:30pm)	2.52 (8.2)			D(2:30-4:30pm)	3.91 (6.0)		
D(1:30-3:30pm)	1.49 (4.9)			D(4:30-6:30pm)	1.91 (2.9)		
D(3:30-5:30pm)	-0.10 (-0.3)			D(6:30-8:30pm)	2.13 (3.0)		
D(5:30-7:30pm)	-0.78 (-2.5)			D(8:30-10:30pm)	3.19 (3.6)		
				D(10:30pm-3am)	1.37 (1.5)		
Social/Recreation		*Social/Recreation*		*Social/Recreation*		*Social/Recreation*	
Variables	Estimates	Variables	Estimates	Variables	Estimates	Variables	Estimates
Constant	1.22 (4.9)	Constant	-0.19 (-0.7)	Constant	-3.08 (-14.5)	Constants	0.75 (2.4)
D(3-6:30am)	-3.53 (-13.0)	D(3-6:30am)	1.46 (3.3)	D(7:30-8:30am)	-0.37 (-1.3)	D(3:00-8:30am)	-0.69 (-1.6)
D(6:30-7:30am)	-4.42 (-16.1)	D(6:30-8:30am)	0.92 (3.0)	D(8:30-9:30am)	0.85 (3.4)	D(8:30-10:30am)	-1.55 (-4.6)
D(7:30-8:30am)	-4.70 (-16.9)	D(8:30-10:30am)	0.03 (0.1)	D(9:30-10:30am)	1.87 (7.5)	D(10:30-12:30pm)	-2.03 (-6.2)
D(8:30-9:30am)	-3.55 (-13.1)	D(10:30am-2:30pm)	-0.36 (-1.3)	D(10:30am-12:30pm)	2.81 (12.2)	D(12:30-2:30pm)	-1.70 (-5.2)
D(9:30-11:30am)	-2.30 (-8.8)	D(2:30-6:30pm)	-0.07 (-0.2)	D(12:30-2:30pm)	3.03 (13.1)	D(2:30-4:30pm)	-1.78 (-5.4)
D(11:30am-1:30pm)	-1.46 (-5.5)	D(6:30-7:30pm)	0.88 (2.9)	D(2:30-4:30pm)	4.30 (18.5)	D(4:30-6:30pm)	-1.30 (-3.8)
D(1:30-3:30pm)	-0.99 (-3.7)	D(7:30-8:30pm)	0.86 (2.7)	D(4:30-6:30pm)	4.19 (16.9)	D(6:30-8:30pm)	-0.55 (-1.6)
D(3:30-5:30pm)	0.20 (0.8)	D(mid to old couples)	0.39 (5.0)	D(6:30-8:30pm)	5.50 (16.6)		
D(5:30-7:30pm)	0.07 (0.3)			D(8:30-10:30pm)	6.33 (10.2)		
D(7:30-9:30pm)	1.29 (5.7)			D(10:30pm-3am)	4.70 (8.4)		
D(history)	-0.80 (-10.2)			D(history)	-0.11 (-2.8)		
Summary Statistics	N=20,928	*Summary Statistics*	N=6,108	*Summary Statistics*	N=52,478	*Summary Statistics*	N=11,929
Final Likelihood	-28232.33	Final Likelihood	-8507.53	Final Likelihood	-90093.69	Final Likelihood	-19052.58
Initial Likelihood	-43518.55	Initial Likelihood	-9830.45	Initial Likelihood	-124685.22	Initial Likelihood	-23212.76
Likelihood w. Const	-38135.64	Likelihood w. Const	-9302.57	Likelihood w. Const	-102731.17	Likelihood w. Const	-20806.40
1-L(F)/L(0)	0.35	1-L(F)/L(0)	0.13	1-L(F)/L(0)	0.28	1-L(F)/L(0)	0.18
1-L(F)/L(C)	0.26	1-L(F)/L(C)	0.09	1-L(F)/L(C)	0.12	1-L(F)/L(C)	0.08

Note: Values in the parentheses are t-ratios. D refers to dummy variable, coded as 1 or 0; brief descriptions in the parentheses identify the condition(s) for which the dummy variable is equal to 1.

as the product of mean probability and total frequency) are provided. χ^2 statistic are then calculated for each cell. In Table 2, if the χ^2 statistic is less than the critical value at $n-1$ degrees of freedom (where n is the number of time periods), the predicted frequency distribution is not significantly different from the actual frequency distribution. The χ^2 statistic associated with each cell also indicates the

activity that contributes most to differences between the predicted and observed distributions.

Table 2 indicates that when the model is applied to the validation set, the overall activity pattern by time of day is captured successfully. An examination of the χ^2 statistics indicates that, without exception, the actual and the expected frequency distributions are not signifi-

TABLE 2   Validation Results for Home-Based Activity Type for Workers and Students

	Workers: HB Return to Work			Workers: NHB Return to Work			Workers: HB Social Recn			Workers: NHB Social Recn		
Time Period	Actual	Expected	χ^2	Actual	Expected	χ^2	Actual	Expected	χ^2	Actual	Expected	χ^2
3:00 am - 5:59 am	0	0	0.00	0	0	0.38	24	31	1.56	0	1	0.81
6:00 am - 7:59 am	1	1	0.00	1	1	0.03	95	101	0.31	3	6	1.76
8:00 am - 9:59 am	7	6	0.26	18	14	1.72	114	122	0.58	29	22	2.28
10:00 am - 11:59 am	14	21	2.13	58	57	0.02	100	100	0.00	42	48	0.63
12 noon - 1:59 pm	149	141	0.41	298	274	2.14	110	108	0.05	73	69	0.17
2:00 pm - 3:59 pm	68	68	0.00	120	109	1.23	163	179	1.39	118	124	0.33
4:00 pm - 5:59 pm	28	25	0.39	31	39	1.59	352	383	2.57	150	154	0.11
6:00 pm - 7:59 pm	18	36	8.91	6	12	3.19	531	555	1.01	149	126	4.10
8:00 pm - 9:59 pm	7	10	1.01	3	6	1.19	152	149	0.07	53	55	0.09
10:00 pm - 2:59 am	10	5	5.56	2	2	0.00	23	33	2.86	27	24	0.30

	Non-Workers: HB Social Recn			Non-Workers: NHB Social Recn [a]			Sample Sizes Used for Model Validation	
Time Period	Actual	Expected	χ^2	Actual	Expected	χ^2		
3:00 am - 6:59 am	19	20	0.07				*Model Type*	*N*
7:00 am - 8:59 am	72	72	0.00	14	16	0.21	HB for Workers	14,494
9:00 am - 10:59 am	101	105	0.13	51	45	0.89	HB for Non-Workers	2,384
11:00 am - 12:59 pm	65	67	0.06	52	58	0.58	NHB for Workers	11,120
1:00 pm - 2:59 pm	36	63	11.52	58	58	0.01	NHB for Non-Workers	4,608
3:00 pm - 4:59 pm	56	59	0.17	48	57	1.40		
5:00 pm - 6:59 pm	71	59	2.24	41	36	0.76		
7:00 pm - 2:59 am	73	66	0.68	29	40	2.79		

[a] The first time period for this model is 3:00 am to 8:59 am.

TABLE 3   Sample Estimation Results for Activity Duration Models (Weibull Distribution)

Full- or Part-time Workers		Full- or Part-time Workers		Non-Workers/Non-Students	
Return to work Variables	Estimates	*Social Recreation* Variables	Estimates	*Social Recreation* Variables	Estimates
Constant	1.29 (44.32)	Constant	0.890 (20.71)	Constant	0.804 (37.48)
D(Male)	0.027 (1.58)	D(Male)	0.076 (3.14)	D(Male)	0.131 (4.38)
D(Full-time Employ)	0.117 (5.07)	D(Full-time Employ)	0.048 (1.75)	History School	-0.0091 (-1.61)
History Work	-0.017 (-3.55)	Age	-0.0036 (-3.88)	History Social/Recn	-0.022 (-2.15)
History Return Work	-0.138 (-12.8)	History Work	-0.017 (-4.69)	D(7:00-9:00 am)	0.281 (5.42)
D(7:00-9:00am)	0.382 (5.16)	History Social/Recn	0.0065 (0.59)	D(9pm-12Midnight)	0.099 (1.08)
D(1:00-4:00pm)	-0.057 (-3.22)	D(Family;Child 5-15 yr)	-0.108 (-3.11)		
D(7:00-9:00pm)	0.248 (3.67)	D(Couple; Wife <35 yr)	-0.166 (-3.26)		
		D(5:00-7:00am)	-0.271 (-3.89)		
		D(7:00-9:00am)	-0.091 (-1.51)		
		D(7:00-9:00pm)	0.029 (0.956)		
		D(9pm-12midnight)	0.106 (2.03)		
γ	1.84 (79.37)	γ	1.15 (97.99)	γ	1.11(84.47)
Summary Statistics	N=4,070	*Summary Statistics*	N=5,369	*Summary Statistics*	N=4,171
Final Likelihood	-4295.327	Final Likelihood	-8997.566	Final Likelihood	-7172.690
Initial Likelihood	-6748.779	Initial Likelihood	-9330.422	Initial Likelihood	-7288.913

Note: 1. Values in the parentheses are t-ratios. D refers to dummy variable, coded as 1 or 0; brief descriptions in the parentheses identify the condition(s) for which the dummy variable is equal to 1.
2. History variables refer to the cumulative past time spent on a certain activity from the beginning of the day to the current activity.

cantly different for all of the six models presented. It is noteworthy that similar results were also obtained for other activity types (tables not shown).

Activity Duration Models

Table 3 presents estimation results for a few activity duration models. These models are estimated assuming that the duration of an activity episode is described by the Weibull distribution.

The Weibull distribution is often used to model the failure time distribution of manufactured components. Analogously, it may be used to model the distribution of the length (duration) of activity episodes. The Weibull density function is convenient in that it provides a wide variety of density curves to model real-life failure time distributions. In addition, unlike the gamma distribution, the Weibull distribution has a closed-form expression for its cumulative distribution function.

In all of the three models presented in Table 3, the model coefficients have the expected sign. History dependence is a significant factor influencing the length of an activity episode. For example, as the cumulative past time spent at work increases, the length of a "return-to-work" activity episode decreases. Similarly, as time spent at work or school increases, the duration of social-recreation activity episodes decreases.

Time-of-day is also found to be a significant factor explaining activity duration. Social-recreation activities are shorter in the morning and longer in the evening for workers. The reverse is true for non-workers, who may often pursue social-recreation opportunities in the morning. Return-to-work activity durations are longest in the morning and late evening but are shorter during midafternoon. Finally, socioeconomic variables such as gender, employment status, age, and household structure are found to influence activity durations.

Validation of the activity duration model (results not presented in the interest of brevity) may be done in a manner similar to that for activity type choice models. The observed and predicted frequency distributions of activity durations by activity type may be compared by using χ^2 test statistics to determine whether the activity duration models are statistically replicating observed activity sojourn patterns.

CONCLUSION

An analytical framework for the development of a procedure for the generation of synthetic activity-travel patterns has been proposed in this paper. As more refined travel demand forecasting and policy analysis are demanded in the current transportation planning contexts, it is becoming inevitable that a new generation of travel demand models will be adopted to satisfy planning needs. Microsimulation of travel behavior is emerging as a promising approach. Many issues, including the generation of synthetic activity-travel patterns, need to be resolved before its practical adaptation, yet only limited knowledge has been accumulated on these issues. In this study attempts have been made to include a broad range of analytical issues and develop a rationale for the proposed approach. It is hoped that the paper has aided in paving the way for the development of a synthetic activity-travel pattern generator and toward the formulation of the next generation of travel demand models.

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