Transportation **27**: 25–51, 2000

Micro-simulation of daily activity-travel patterns for travel demand forecasting*

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Key words: forecasting, daily activity-travel patterns, micro-simulation, synthetic travel patterns

Abstract. The development and initial validation results of a micro-simulator for the generation of daily activity-travel patterns are presented in this paper. The simulator assumes a sequential history and time-of-day dependent structure. Its components are developed based on a decomposition of a daily activity-travel pattern into components to which certain aspects of observed activity-travel behavior correspond, thus establishing a link between mathematical models and observational data. Each of the model components is relatively simple and is estimated using commonly adopted estimation methods and existing data sets. A computer code has been developed and daily travel patterns have been generated by Monte Carlo simulation. Study results show that individuals' daily travel patterns can be synthesized in a practical manner by micro-simulation. Results of validation analyses suggest that properly representing rigidities in daily schedules is important in simulating daily travel patterns.

1. Introduction

Urban passenger travel demand has traditionally been forecast based on deterministic models that pertain to four aspects of daily travel: the number of trips, the origin and destination of each trip, the mode of travel, and the route of travel. Conventional four-step procedures which predict these four aspects by sequentially placed four model components, have been critiqued in the past from various viewpoints. For example, Dickey notes that "[the traditional four-step travel-demand estimation process] is cumbersome, expensive, and requires a large amount of data. . . . The generation of trips is independent of the transportation supply characteristics and possible technological

* An earlier version of this paper was presented at the 8th Meeting of the International Association for Travel Behavior Research, Austin, Texas, September 21–25, 1997.

improvements, and the models are generally site-specific – that is, they are not transferable from one urban area to another" (Dickey 1983, p. 227). When discrete choice models were being introduced into the transportation planning field, it was argued that the aggregate models are not data efficient, susceptible of biases due to ecological correlations, not transferable due to the use of zone systems, too rigidly structured and as a result not policy sensitive, and not supported by behavioral theories (e.g. Domencich & McFadden 1975; Spear 1977; Tye et al. 1982). Oppenheim (1995) notes that "the conventional approach is not based on any single unifying rationale that would explain or legitimize all aspects of demand jointly . . ." and that the sequential model structure is incapable of properly representing the effects of congestion without feedback loops, which are computationally inefficient and "may or may not converge to a stable distribution."

The following two assumptions have played critical roles in the development of the four-step procedures: 1) each trip can be analyzed independently of the other trips made by the same individual, and 2) the time-of-day dimension can be ignored in the analysis. As a result of these assumptions, it was possible to develop practical demand forecasting procedures within the limited computational and data-handling capabilities of the 50s and 60s. The ability of the four-step procedure in replicating and forecasting daily travel patterns, however, is limited as a result. For example, trip chaining is not at all represented in the trip-based four step procedures. As a consequence, modal shift may be erroneously forecast by them (Kitamura, 1997). Although "Dissatisfaction with trip-based forecasting tools and attempts to move practice toward activity-based approaches predate the milestone legislation of the 1990s in the US" (Goulias 1997), practical methods of demand forecasting and policy analysis have been predominantly trip-based.

On the second assumption, it is curious why the time dimension was entirely omitted in the four-step procedures when the main preoccupation of urban transportation planning – congestion – has to do with the concentration of demand in space and time. The lack of a time axis in the analytical framework implies a lack of coherent procedures to predict travel demand by time of day. For example, peak spreading cannot be dealt with without devising a procedure, outside the framework of the four-step procedures, to assign trips to different periods of the day. Furthermore, recent emphases on environmental impacts of urban transportation have intensified the needs to introduce the time dimension into travel demand forecasting procedures. Weiner (1993) lists as emissions modeling requirements the following six items: 1) VMT by hour of the day by grid square, 2) average speeds by hour by grid location, 3) vehicle mix by hour of the day by grid square, 4) proportion of cold starts by hour of the day, 5) seasonal variation in VMT, vehicle mix, etc., and 6) annual growth in VMT. These requirements call for methodologies by which:

- trip starting time and ending time can be determined in a logically coherent manner;
- elapsed time between successive two trips by the same vehicle can be estimated such that whether the latter trip involves a cold start can be determined;
- vehicle type is explicitly treated; and
- day-to-day variations and seasonal variations in travel demand are appropriately captured.

It would be obvious that the introduction of the time dimension is critical to address the first two issues (Kitamura 1997).

In sum, with the recent emphases on the environment and resource consumption, travel demand management (TDM), distribution of costs and benefits, and other social issues, current urban transportation planning contexts demand refined tools for forecasting and policy analysis. Spatial and temporal characteristics of travel demand need be more precisely and accurately represented. The conventional four-step procedures are unlikely to be able to satisfy the current requirements.

Many alternative approaches have been proposed in which attempts were made to treat daily travel behavior in its entirely (e.g. Adler & Ben-Akiva 1979; Bhat & Koppelman 1994; Pas 1983; Recker 1995; Recker et al. 1986). Two major approaches taken in these studies are: application of discrete choice models, and application of mathematical programming concepts. Treating daily travel behavior within the framework of discrete choice analysis may not be effective because, with the spatial and temporal dimensions, the choice set becomes astronomically large if one wishes to gain adequate levels of precision in forecasts. Treating the decision process underlying daily behavior as a mathematical programming problem, on the other hand, is not tractable for two reasons. First, the decision process deals with an extremely complex problem to formulate and to find a solution for, leading to prohibitive computational requirements. Secondly, it is unlikely that human decision making can be adequately formulated as mathematical optimization problems.

The approach taken in this study is the micro-simulation of individual daily activity-travel behavior. It has been noted earlier (Kitamura et al. 1997) that

> "Micro-simulation of the behavior of a household or an individual is drawing attention as a new approach to travel demand forecasting (Miller 1996). Micro-simulation 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; inter-personal interactions; multiple planning horizons; and complexity of activity-travel decision making as a scheduling problem (Pas 1990). Micro-simulation is an effective approach to such a complex phenomenon which facilitates its practical, yet realistic, representation."

A sequential, simulation approach to the generation of daily activity-travel patterns is presented in this paper. In this approach, a daily activity-travel pattern is decomposed into components to which certain aspects of observed activity-travel behavior correspond, thus establishing a link between mathematical models and observational data. Each of the model components is relatively simple and is estimated using commonly adopted estimation methods and existing data sets. A computer code has been developed and daily travel patterns have been generated by Monte Carlo simulation.

The development of the model system and initial results of model validation are presented in this paper. The objectives of this paper are two-fold. Firstly, it aims at demonstrating that individuals' daily travel patterns can be synthesized in a practical manner by Monte Carlo simulation. Secondly it attempts to examine discrepancies between observed and simulated travel patterns and show that properly representing rigidities in daily schedules is important in simulating daily travel patterns. The latter point is an inference obtained from the results of the validation analyses so far conducted. The simulator is still under development and the intent of this paper is to report on the structure of the simulator and on behavioral insights so far obtained from the ongoing development effort.

Representation of daily activity-travel patterns is first discussed and the structure of the sequential model system is presented formally in Section 2. The respective model components are described in Section 3. Section 4 reports on the results of initial validation studies of the model system, using the 1991 household survey results provided by the Southern California Association of Governments (SCAG). Section 5 is a brief conclusion.

2. Representation of daily activity-travel patterns

The daily activity-travel pattern of an individual, i, is composed of a series of activities and trips. let

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

represent individual i's daily pattern, where

X_{ij} = the type of the j-th activity (or a bundle of activities) pursued by individual i (excluding travel),
T_{ij} = the duration of the j-th activity pursued by individual i,
L_{ij} = the location of the j-th activity pursued by individual i,
M_{ij} = the mode of travel used to reach the j-th activity location, and
n = the number of activities involved in individual i's daily activity-travel pattern,

and (X_{i0}, T_{i0}, L_{i0}, M_{i0}) is the initial condition. The X_{ij}'s are defined here to collectively refer to the bundle of activities pursued at a location. Consequently there is a trip between every pair of successive activities, and $L_{ij} \neq L_{i,j+1}$ for $j = 0, 1, \ldots, n-1$. This definition is introduced purely because of the presentational simplicity it offers, and the modeling framework described in this paper is in principle applicable with a more activity-based definition of the X_{ij}'s where they refer to respective episodes of activity engagement irrespective of their locations.

An individual's activity-travel pattern varies from day to day. It is viewed in this study that this variation is random, and each possible pattern occurs with a certain probability. The approach taken in this study is to establish these probabilities and generate ($\mathbf{X}_i$, $\mathbf{T}_i$, $\mathbf{L}_i$, $\mathbf{M}_i$) according to the probabilities through Monte Carlo simulation. Now, consider the following identity:

$$\begin{aligned}
&\Pr[\mathbf{X}_i, \mathbf{T}_i, \mathbf{L}_i, \mathbf{M}_i] \\
&= \Pr[X_{i0}, X_{i1}, \ldots, X_{in}; T_{i0}, T_{i1}, \ldots, T_{in}; L_{i0}, L_{i1}, \ldots, L_{in}; M_{i0}, M_{i1}, \ldots, M_{in}] \\
&= \Pr[X_{in}, T_{in}, L_{in}, M_{in} | X_{i0}, X_{i1}, \ldots, X_{i,n-1}; T_{i0}, T_{i1}, \ldots, T_{i,n-1}; \\
&\quad L_{i0}, L_{i1}, \ldots, L_{i,n-1}; M_{i0}, M_{i1}, \ldots, M_{i,n-1}] \\
&\quad \times \Pr[X_{i,n-1}, T_{i,n-1}, L_{i,n-1}, M_{i,n-1} | X_{i0}, X_{i1}, \ldots, X_{i,n-2}; \\
&\quad T_{i0}, T_{i1}, \ldots, T_{i,n-2}; L_{i0}, L_{i1}, \ldots, L_{i,n-2}; M_{i0}, M_{i1}, \ldots, M_{i,n-2}] \\
&\quad \times \ldots \times \Pr[X_{i0}, T_{i0}, L_{i0}, M_{i0}].
\end{aligned} \tag{2}$$

Namely, the simultaneous probability associated with ($\mathbf{X}_i$, $\mathbf{T}_i$, $\mathbf{L}_i$, $\mathbf{M}_i$) = (X_{i0}, X_{i1}, . . . , X_{in}; T_{i0}, T_{i1}, . . . , T_{in}; L_{i0}, L_{i1}, . . . , L_{in}; M_{i0}, M_{i1}, . . . , M_{in}) can be expressed as a product of a series of conditional probabilities,

$$\begin{aligned}
&\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | X_{i0}, X_{i1}, \ldots, X_{i,j-1}; T_{i0}, T_{i1}, \ldots, T_{i,j-1}; \\
&\quad L_{i0}, L_{i1}, \ldots, L_{i,j-1}; M_{i0}, M_{i1}, \ldots, M_{i,j-1}], \quad j = 1, 2, \ldots, n.
\end{aligned} \tag{3}$$

In this conditional probability, the attributes of the next activity are dependent on the past history of activity engagement and travel (types of activities engaged, X_{i0}, X_{i1}, . . . , $X_{i,j-1}$; their durations, T_{i0}, T_{i1}, . . . , $T_{i,j-1}$; and locations, L_{i0}, L_{i1}, . . . , $L_{i,j-1}$). Note that the T_{ij}'s collectively define the clock time when the j-th activity starts as

$$t_0 + T_{i0} + d(L_{i0}, L_{i1}, M_{i1}, t_{i0}) + T_{i1} + d(L_{i1}, L_{i2}, M_{i2}, t_{i1}) + T_{i2} + \ldots + \\ + d(L_{i,j-2}, L_{i,j-1}, M_{i,j-1}, t_{I,j-2}) + T_{i,j-1}, \qquad (4)$$

where $d(p, q, m, t)$ is the travel time from p to q by mode m starting at clock time t, and t_0 is the clock time at the beginning of the study period. The attributes of the next activity are therefore time-of-day dependent. Note that travel time is assumed in this study to be static and determinable given the origin, destination, mode used and starting time.

For notational simplicity, let $\mathbf{H}_{ij}$ represent the portion of the daily pattern up to the j-th activity, namely:

$$\mathbf{H}_{ij} = (X_{i0}, X_{i1}, \ldots, X_{ij}; T_{i0}, T_{i1}, \ldots, T_{ij}; L_{i0}, L_{i1}, \ldots, L_{ij}; \\ M_{i0}, M_{i1}, \ldots, M_{ij}) \qquad (5)$$

Then one can further decomose $\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | \mathbf{H}_{i,j-1}]$ as

$$\begin{aligned} &\Pr[X_{ij}, T_{ij}, M_{ij} | \mathbf{H}_{i,j-1}] \\ &\quad = \Pr[X_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[T_{ij} | X_{ij}, \mathbf{H}_{i,j-1}] \times \\ &\quad\quad \Pr[L_{ij} | X_{ij}, T_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | X_{ij}, T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}] \\ &\quad = \Pr[L_j | \mathbf{H}_{i,j-1}] \times \Pr[X_{ij} | L_{ij}, \mathbf{H}_{i,j-1}] \times \\ &\quad\quad \Pr[T_{ij} | L_{ij}, X_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | X_{ij}, T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}] \\ &\quad = \Pr[T_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[L_{ij} | T_{ij}, \mathbf{H}_{i,j-1}] \times \\ &\quad\quad \Pr[M_{ij} | T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[X_{ij} | T_{ij}, L_{ij}, M_{ij}, \mathbf{H}_{i,j-1}] \\ &\quad = \ldots \text{ etc.} \end{aligned} \qquad (6)$$

With these alternative decompositions, the probability of a daily pattern, $\Pr[\mathbf{X}_i, \mathbf{T}_i, \mathbf{L}_i, \mathbf{M}_i]$, can be expressed as a series of conditional probabilities that correspond to traditional travel choice models such as mode choice and destination choice models. The following decomposition schemes are used in the Synthetic Travel Pattern Generator (STPG) developed in this study:

If $L_{i,j-1}$ = home base:

$$\begin{aligned} &\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | \mathbf{H}_{i,j-1}] \\ &\quad = \Pr[\mathrm{X}_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[T_{ij} | X_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[L_{ij} | X_{ij}, T_{ij}, \mathbf{H}_{i,j-1}] \times \\ &\quad\quad \Pr[M_{ij} | X_{ij}, T_{ij}, L_{ij}, \mathbf{H}_{i,j-1}]. \end{aligned} \qquad (7a)$$

If $L_{i,j-1} \neq$ home base:

$$\begin{aligned} &\Pr[X_{ij}, T_{ij}, L_{ij}, M_{ij} | \mathbf{H}_{i,j-1}] \\ &\quad = \Pr[X_{ij} | \mathbf{H}_{i,j-1}] \times \Pr[T_{ij} | X_{ij}, \mathbf{H}_{i,j-1}] \times \Pr[M_{ij} | X_{ij}, T_{ij}, \mathbf{H}_{i,j-1}] \times \\ &\quad\quad \Pr[L_{ij} | X_{ij}, T_{ij}, M_{ij}, \mathbf{H}_{i,j-1}]. \end{aligned} \qquad (7b)$$

The attributes of j-th activity are thus determined by probabilistic models representing

- activity type choice,
- activity duration choice,
- activity location (destination) choice, and
- travel mode choice.

The decomposition scheme takes on the form of a trip-interchange model in the first case where the location of the preceding activity ($L_{i,j-1}$) is the home base, while it assumes the form of a trip-end model when $L_{i,j-1}$, is not the home base. This reflects the consideration that the choice of mode for a trip which starts from a non-home origin is strongly conditioned by the mode taken for the preceding trip; it is therefore likely that the destination of the trip is conditioned on the mode used.

The model components of the STPG system developed in this study have a number of unique features which are discussed in the next section. Additional discussions on the model system, modeling issues, and sample estimation results of the activity choice models and activity duration models can be found in Kitamura et al. (1997). The properties of the destination choice models adopted in the system are discussed in detail in Kitamura, Chen et al. (1998). The mode choice component is one of the focuses of the next section.

3. Model components

The above four groups of models are specified for different segments of individuals and trips as defined in Table 1. A "home-based" model in this study refers to a model that is concerned with a trip originating from the home base (e.g. a home-based mode choice model) or one concerned with an activity whose location is reached from the home base (a home-based activity type choice model, or a home-based activity location choice model). A "non-home-based" model, on the other hand, refers to a model that deals with a trip originating from a non-home location or an activity which is reached from a non-home location. A non-home-based model in this study is thus not necessarily concerned with non-home-based trips as traditionally defined.

In addition, the following model components are included in the STPG:

- work/school location models,
- initial departure timing models, and
- initial location models.

The first group of models determines the work or school location for each individual who is employed or a student. The models are formulated as multinomial logit models which can be considered to belong to the family of production-

Table 1. Segmentation of major model components.

Model group	Segmentation base		
	Employment[1]	Base[2]	Activity type[3]
Activity type choice	×	×	
Activity duration	×		×
Activity location choice	×	×	×
Mode choice		×	

[1] Worker vs. Non-worker.
[2] Home-based vs. Non-home-based.
[3] Defined when the respective models are discussed in text.

constrained gravity models. The initial departure timing models are simple probability distribution models for T_{i0}. The timing of the first trip of the day is determined by these models in the STPG. The initial location models are also simple probabilistic models that depict the location of each individual at t_0. In this study, a 24-hour period from 3:00 AM to 2:59 AM of the following day, is set as the study period. Therefore 3:00 AM is adopted as t_0, at which time 98% of the individuals in the sample used for model estimation were at the home base.

In the rest of this section, the activity type choice models, duration models, destination choice models and mode choice models are discussed. The following notation will be used in the discussion in addition to the set of variables that have been defined so far:

t_{ij} = the time of the day when the j-th activity of individual i is completed,
$\mathbf{Z}_i$ = a vector of variables representing attributes of individual i and those of the household to which individual i belongs,
h_i = the residence location of individual i,
w_i = the work of school location of individual i,
SD = a vector of variables representing demographic and socio-economic characteristics of the study area,
LU = a vector of variables representing land use characteristics of the study area, and
TR = a vector of variables representing transportation network and travel time characteristics of the study area.

The model components have been estimated using the results of the 1991 home interview travel survey conducted by SCAG, along with accompanying land use and network data defined for 1,527 traffic analysis zones (TAZs).[1] Because of the size of the data set, some models have been estimated using sub-samples of randomly selected individuals or trips from the original survey sample.

3.1. *Activity type choice models*

These models determine probabilistically the type of the next activity in the STPG. Table 2 presents the activity types that are used to define the choice sets of the four model components in the system. Because a standard trip record file maintained by a metropolitan planning organization (MPO) is used in the estimation of the model components of this study, these activity types are defined in terms of trip purpose categories. Non-work activities are classified into: school, social/recreational, shopping, personal business, eat out, and other (the "other" category includes primarily "serve passenger" purposes). The choice set of the home-based model for non-workers may contain these activity types.

Three additional activity types are introduced into the home-based model for workers, which are: work, work-related, and return to work location. Two "home" states are introduced into the non-home-based models. The first of the two, "home – transient," refers to in-home activities pursued in a temporary stay at the home base; it represents the case where the individual returns home temporarily to leave home again within the study period. The other, "home – absorbing," implies a final return to the home base for the study period.

Choice sets formulated in STPG simulation runs are subject to various constraints and do not necessarily contain all the activity types shown in Table 2. For the home-based model for workers, the constraints include: 1) "return to work" can be included only after "work" has been chosen; and 2) "work" cannot be included once "work" has been chosen. For the non-home-based model for workers, the constraints include, in addition to 1) and 2) above,

Table 2. Choice sets of activity type choice models.

Home-based models		Non-home-based models	
Workers	Non-workers	Workers	Non-workers
Work	School	Home – transient	Home – transient
Work-related	Social/recreational	Home – absorbing	Home – absorbing
Return to work	Shopping	Work	School
School	Personal business	Work-related	Social/recreational
Social/recreational	Eat out	Return to work	Shopping
Shopping	Other	School	Personal business
Personal business		Social/recreational	Eat out
Eat out		Shopping	Other
Other		Personal business	
		Eat out	
		Other	

3) “return to work” and “work” are not included in the choice set if the previous activity is “work” or “return to work”.

The activity type choice models in STPG can be described as follows:

$$\Pr[X_{ij} = a \,|\, \mathbf{H}_{i,j-1}] = F(a\colon t_{i,j-1}, L_{i,j-1}, \mathbf{D}_{i,j-1}, \mathbf{Z}_i, \Psi_{ij}), \ {}^{\forall}a \in \psi_{ij}, \tag{8}$$

where

$\mathbf{D}_{i,j-1}$ = a vector of variables representing the history of activity engagement by individual i up to the $(j-1)$th activity, and
Ψ_{ij} = the set of activity types available for the j-th activity.

The variable, $L_{i,j-1}$, serves as a home vs. non-home indicator in the models developed in this study. All activity type choice models are formulated as multinomial logit models.

Estimation results indicate that the time of day variable, $t_{i,j-1}$, is the predominant factor that influences activity types. Simple representations of activity history are adopted in these models, with $\mathbf{D}_{i,j-1}$ specified as dummy variables that indicate whether activities of respective types have been engaged. Indications have been obtained that personal business is positively history dependent, i.e. the probability of engaging in a personal business activity is larger if the same type of activity has been engaged in the past. Shopping and social/recreational have been found to be negatively history dependent. For details, see Kitamura and Chen (1996).

3.2. *Activity duration models*

The activity duration models take on the form,

$$\Pr[T_{ij} \le s \,|\, X_{ij} = a, \mathbf{H}_{i,j-1}, \mathbf{Z}_i] = G(s\colon a, t_{i,j-1}, \mathbf{D}_{i,j-1}, \mathbf{Z}_i), \ s > 0. \tag{9}$$

Weibull distribution models of the following form are exclusively used in this study for all activity types:

$$P_T(t) = \frac{\gamma}{\alpha_i}\left(\frac{t}{\alpha_i}\right)^{\gamma-1} \exp\left[-\left(\frac{t}{\alpha_i}\right)^{\gamma}\right], \ t > 0, \tag{10a}$$

$$\alpha_i = \exp(\theta' X_i), \tag{10b}$$

where $P_T(t)$ represents a cumulative distribution, θ is a vector of coefficients, X_i is a vector of explanatory variables (i.e. $t_{i,j-1}$, $\mathbf{D}_{i,j-1}$, and $\mathbf{Z}_i$), and γ is a “shape” parameter. If γ takes on a value of 1, the distribution reduces to a negative exponential distribution. The mean and variance of the distribution are given respectively as

$$E[T] = \alpha_i\Gamma(1 + \gamma^{-1}) = \exp(\beta' X_i)\Gamma(1 + \gamma^{-1}), \tag{11a}$$

$$\mathrm{Var}(T) = \exp(2\beta' X_i)\{\Gamma(1 + 2\gamma^{-1}) - \Gamma^2(1 + \gamma^{-1})\}. \tag{11b}$$

Note that the mean and variance are assumed to be different from observation to observation according to the value of X_i.

Two sets of activity duration models are developed for workers and non-workers separately. The same sets of activity types as in Table 2 are adopted for both workers and non-workers, except for that no models are developed for "home – absorbing." Included as explanatory variables are: selected demographic, socio-economic variables, dummy variables representing the time of day ($t_{i,j-1}$) and cumulative amounts of time spent on types of activities in the past ($D_{i,j-1}$). For estimation results, see Kitamura and Chen (1996).

3.3. *Activity location (destination) choice models*

An activity-location (or destination) choice model predicts the probability that a particular location will be chosen from among the universe of alternative locations. The home-based model is formulated as follows:

$$\begin{aligned} \Pr[L_{ij} &= \omega | X_{ij} = a,\ T_{ij} = s,\ \mathbf{H}_{i,j-1},\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega] \\ &= D(\omega{:}\ a,\ s,\ t_{i,j-1},\ L_{i,j-1},\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega),\ {}^{\forall}\omega \in \Omega, \end{aligned} \tag{12}$$

where Ω is the set of all possible destination locations. The non-home-based model can be summarized as

$$\begin{aligned} \Pr[L_{ij} &= \omega | X_{ij} = a,\ T_{ij} = s,\ M_{ij} = m,\ \mathbf{H}_{i,j-1},\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega] \\ &= D(\omega{:}\ a,\ s,\ m,\ t_{i,j-1},\ L_{i,j-1},\ h_i,\ \mathbf{Z}_i,\ \mathbf{SD},\ \mathbf{LU},\ \mathbf{TR},\ \Omega),\ {}^{\forall}\omega \in \Omega. \end{aligned} \tag{13}$$

The destination choice models are formulated in this study as multinomial logit models by activity type and by trip origin (home base vs. others). Activity types are aggregated here into five types: work-related, social/recreation or shopping, eat meal, personal business, and others. Note that work and school destinations are determined by the work and school location models in the STPG; no destination choice models are therefore applied to work, school, and return-to-office trips in the model system.

All person and household attributes (elements of $\mathbf{Z}_i$) are multiplied by the zone-to-zone travel time. This represents the assumption that the effect of spatial separation varies across individuals of different attributes. Estimation results support this assumption. Zonal attraction measures such as retail employment, as well as inter-zonal travel time, show highly significant effects that can be theoretically supported.

The destination choice models are developed in the study in part to test the following hypotheses:

1. time-of-day affects destination choice behavior;
2. the duration of stay at the destination affects destination choice, and
3. home location affects non-home-based destination choice.

The statistical results offer strong evidence in support of the hypotheses. The results indicate that the distance to a destination tends to be shorter in later parts of the day; individuals tend to travel farther for activities that take longer, and tend to find closer destinations for shorter activities; and the destination-to-home travel time is as significant and have roughly as much effect on non-home-based destination choice as the origin-to-destination travel time. The last finding confirms the earlier results by Kitamura and Kermanshah (1984). For further discussion, see Kitamura, Chen et al. (1998).

3.4. *Mode transition models*

As noted earlier, the STPG adopts the trip-interchange scheme for home-based destination and mode choice, while the trip-end scheme is adopted for non-home-based mode and destination choice. The SCAG model choice models are adopted for home-based trips in the current version of STPG (see *SCAG Regional Mode Choice Model Development Project*, Final Report, October 28, 1996). The discussion here therefore focuses on the non-home-based mode choice models of the STPG, which comprise a series of mode transition matrices.

The current version of non-home-based mode choice models can be summarized as:

$$\begin{aligned} \Pr[M_{ij} = m \,|\, X_{ij} = a,\ T_{ij} = s,\ \mathbf{H}_{i,j-1},\ \mathbf{Z}_i,\ \mathbf{TR},\ \Theta_{ij}] &= \Pr[M_{ij} = m \,|\, M_{i,j-1} = m',\ t_{i,j-1},\ L_{i,j-1},\ C_{i,j-1},\ O_i,\ \Theta_{ij}] \\ &= Q(m\!: m',\ t_{i,j-1},\ L_{i,j-1},\ C_{i,j-1},\ O_i,\ \Theta_{ij}), \end{aligned} \tag{14}$$

where

Θ_{ij} = the set of travel modes available to reach the j-th activity site,
$C_{i,j-1}$ = the location of individual i's personal vehicle at the time of the j-th activity, and
O_i = the employment status of individual i.

In the non-home-based mode choice models of this study, $L_{i,j-1}$ is treated as a binary indicator of whether it is the work/school base of individual i; $C_{i,j-1}$ that of whether individual i's personal vehicle is parked at the work/school base; and O_i that of whether individual i is employed or a student.

The focus of the approach here is on modal transition.[2] The models are not differentiated by trip purpose, nor are any indicators of levels of service included. The approach emphasizes the availability of a personal vehicle and the likelihood of leaving a personal vehicle behind. The latter is assumed to be high when the individual is at the work/school base. This approach was adopted primarily because the STPG was originally conceived as a tool to generate synthetic travel patterns for synthetic households and thereby create a database of household, person and travel patterns for synthetic households and thereby create a database of household, person and trip attributes that are comparable to those in travel survey data bases that are typically maintained by MPOs. If the STPG is to be applied as a tool for forecasting or policy analysis, then the non-based mode choice models may be modified for increased policy sensitivity.

Modal transition probability matrices are presented for workers and non-workers in Table 3. The table is based on a tabulation of the primary mode of each trip, and does not represent the linkages of travel modes within a trip (e.g. walk to a bus stop, bus to a rail station, rail to downtown, walk to the office). The matrix for workers exhibits clearly that model transition tends to be homogeneous with transitions within the same mode predominating.

Table 3. Non-home-based modal transition matrices.

"From" mode	"To" mode				Total	
	Driver	Passenger	Transit	Walk/Bike	P	N
Workers						
Auto driver	0.921	0.057	0.001	0.021	1.000	42,197
Auto passenger	0.250	0.687	0.020	0.043	1.000	16,278
Public transit	0.024	0.176	0.702	0.098	1.000	1,720
Walk/Bike	0.173	0.122	0.024	0.681	1.000	5,212
Total	0.671	0.222	0.026	0.081	1.000	65,407
Non-workers						
Auto driver	0.903	0.066	0.001	0.030	1.000	16,207
Auto passenger	0.881	0.101	0.005	0.013	1.000	781
Public transit	0.705	0.045	0.250	–	1.000	44
Walk/Bike	0.870	0.049	0.002	0.079	1.000	547
Total	0.901	0.067	0.001	0.031	1.000	17,579

In fact nearly 84% (54,835) of the observed 65,407 transitions involve one mode, most notably from auto driver to auto driver (59.4% of total).

Although observed frequencies are not presented in the table, transitions are in fact relatively symmetric. For example, there are 906 transitions observed from auto driver to bike/walk, versus 901 from bike/walk to auto driver; 318 from auto passenger to public transit, versus 302 from public transit to auto passenger. One notable exception is the transition between auto driver and auto passenger: 2,384 transitions observed from auto driver to auto passenger, versus 4,063 from auto passenger to auto driver. More detailed analysis is required to determine what has caused this asymmetry.

The diagonal elements of the transition probability matrix for non-workers are smaller than those of the matrix for workers. Yet in fact about the same percentage (84.0%) of the 17,579 transitions are within the same mode. Auto driver is a more dominant travel model for non-workers than for workers, at least in this data set from the Los Angeles metropolitan area. There are only 177 transitions (1.01% of the total) in the data file that do not involve auto driver. Interestingly the non-workers' matrix shows an opposite asymmetry in the transition between auto driver and auto passenger: 1,073 transitions from auto driver to auto passenger, versus 688 from auto passenger to auto driver.

Although the tables here are not differentiated by base and parking location, the simulation of activity-travel patterns by the STPG accounts for whether the transition is taking place at the work/school base, and whether the personal vehicle has been parked at the work/school base. This is believed to have given additional realism to the simulation of non-home-based mode choice.

4. Validation study

The STPG is currently under development and its components are undergoing the process of continuous validation and improvement. Presented in this section are results of validation studies that were performed in phases using different samples. First, results of a validation study of the activity type choice models are presented. Results of a study based on simulation runs of the entire STPG system are then presented. No model components have been "calibrated," namely, coefficient values obtained from statistical estimation are used as they are without any adjustment.

4.1. *Activity generation*[3]

Because of the large sample size of the SCAG data set used in the study, it was possible to split the original sample into two sub-samples of approximately equal size and use one for model estimation and the other for validation. In the validation study, the 24-hour study period was divided into 7 to 10 periods, depending on the sample size and temporal distribution of activity starting times. For each period, the choice probability of each activity type for each individual in the validation data set was computed using the applicable model, with the coefficient estimates obtained from the estimation data set and an explanatory variable vector derived from the validation data set. The predicted choice probabilities were aggregated and treated as the expected frequencies of activity types, and were compared with the observed frequencies of activity types in the validation data set.

Table 4 presents a summary of validation results by time periods for the four activity-type choice models. As a goodness-of-fit measure, a chi-square statistic is shown for each time period. Considering that the chi-square statistics are often based on very large samples, the results suggest that overall the models are performing well, especially those for non-workers. Notable, however, is the significant chi-square values found for the worker's models in most of the time periods after 12:00 noon. In the case of the home-based model for workers, for example, work and school activities are often under- or over-estimated, especially between 2:00 PM and 7:59 PM. Presumably these discrepancies are caused by the fact that the STPG incorporates no mechanism to represent fixities in individuals' daily activity-travel patterns, such as work and school schedules.

The results nonetheless indicate that the activity choice models developed in the study, especially those for non-workers, well capture salient characteristics of activity engagement over the 24-hours period. Such systematic discrepancies as noted above at the same time warrant critical examination of the modeling approach taken here. As noted above, it would be productive to examine alternative model structures where fixities in activity schedules can be represented. It is also worthy to note that the models are formulated as history dependent models, but do not necessarily take on the form of Markovian models of activity type transition as was often done in the past (e.g. Hanson & Marble 1971; Horton & Shuldiner 1967; Kitamura 1983; Kondo 1974; Nystuen 1967; Sasaki 1972). This may be an effective approach to accounting for such typical activity sequences as work $\rightarrow$ eat meal $\rightarrow$ return to work $\rightarrow$ home. It may also be effective in representing the tendencies in activity sequencing that activities of more mandatory nature tend to be pursued first (Kitamura 1983).

Another factor that deserves attention is constraints on activity and travel. The modeling approach of this study does not account for space-time constraints that govern individuals' movement. A micro-simulation model system that explicitly incorporates Hägerstrand's prism constraints (Hägerstrand 1970) has been developed (Kitamura & Fujii 1998) and applied to evaluate the

Table 4. Validation results: Activity choice model.

Workers

Period	Home-based χ^2	Home-based N	Non-home-based χ^2	Non-home-based N
3:00 – 5:59 AM	16.31*	442	–	26
6:00 – 7:59 AM	7.21	4023	9.59	302
8:00 – 9:59 AM	11.54	3950	11.56	609
10:00 – 11:59 AM	14.53	966	4.93	848
12:00 – 1:59 PM	18.69*	868	27.25**	1580
2:00 – 3:59 PM	34.71**	993	24.72**	2108
4:00 – 5:59 PM	29.43**	1198	22.72**	2526
6:00 – 7:59 PM	49.59**	1545	19.76**	1706
8:00 – 9:59 PM	15.87*	410	16.75*	863
10:00 PM – 2:59 AM	13.20	99	7.62	552

All χ^2 statistics have 8 degrees of freedom
*: Significant at $\alpha = 0.05$.
**: Significant at $\alpha = 0.01$.

Non-workers

Home-based Period	χ^2	N	Non-home-based Period	χ^2	N
3:00 – 6:59 PM	3.44	65	3:00 – 8:59 AM	10.36	240
7:00 – 8:59 AM	4.76	373	9:00 – 10:59 AM	15.42*	596
9:00 – 10:59 AM	9.28	548	11:00 AM – 12:59 PM	12.15	963
11:00 AM – 12:59 PM	7.62	383	1:00 – 2:59 PM	3.23	845
1:00 – 2:59 PM	16.47*	368	3:00 – 5:59 PM	11.67	933
3:00 – 4:59 PM	3.91	274	5:00 – 6:59 PM	11.30	490
5:00 – 6:59 PM	8.98	221	7:00 PM – 2:59 AM	14.83*	541
7:00 PM – 2:59 AM	3.16	152			

All χ^2 statistics have 6 degrees of freedom.
*: Significant at $\alpha = 0.05$.
**: Significant at $\alpha = 0.01$.

effectiveness of alternative TDM measures in regional CO_2 emissions reduction (Kitamura, Fujii et al. 1998). Incorporation of indicators of constraints and accessibility is one of the directions for the future extension of the STPG system.

4.2. *Initial system validation*

The STPG system as a whole, with all its components incorporated, is tested by comparing observed daily travel patterns and simulated patterns. In this validation study a sample of 3,500 individuals was randomly drawn from the SCAG data base.[4] Based on the demographic and socio-economic characteristics of each of the 3,500 individuals and land use and network data supplied by SCAG, the STPG system was deployed to simulate daily activity-travel patterns for the 3,500 individuals. The predicted activity-travel patterns were then compared to the observed activity patterns. This comparison was carried out with respect to various aspects of activity-travel patterns. Note that the simulation here represents no policy scenarios.

Activity-travel patterns are simulated by the STPG as follows. First, data on the attributes of the individual and household (including the residence zone) are input. Given this information, a work (or school) zone is selected for a worker (or a student) using the work (or school) location model by Monte Carlo simulation. An initial location of the individual at t_0 and an initial departure time (= $t_0 + T_{i0}$) are then simulated. Following this, (X_{ij}, T_{ij}, L_{ij}, M_{ij}) are generated activity by activity using the model components described in Section 3. The simulation process ends for the individual when "home-absorbing" is selected by the activity type choice model, or when $t \geq 27$ (= 3:00 AM of the following day).

Table 5 compares the number of trips between the SCAG sample and STPG simulation. The STPG over-predicts the number of trips by 19.0%; the number of trips per person in the SCAG sample is 4.40, while the simulated number is 5.23. The table also indicates that the STPG under-estimates the number of home-originated trips by 13.5%, and over-estimates non-home-originated trips by 44%. The primary reason for this discrepancy is suspected to be the aforementioned absence of a mechanism in the STPG to represent fixities in individuals' daily activity-travel patterns.

Table 6 presents the distribution of trip purposes. A comparison of the observed and simulated frequencies indicates that the over-prediction of the total trip frequency in the STPG simulation is due to the over-prediction of

Table 5. Number of trips: Observed vs. simulated.

	SCAG observed	STPG simulated
Number of Trips	15,384	18,303
Home-Originated	6,738	5,831
Non-Home-Originated	8,646	12,472
Trips per Person	4.40	5.23

Table 6. Distribution of trip purposes: Observed vs. simulated.

A. *All individuals*

	SCAG observed		STPG simulated	
	Frequency	%	Frequency	%
Home	5,353	34.8	5,879	32.1
Work[1]	2,268	14.7	3,318	18.1
Work-related	426	2.8	649	3.6
School	845	5.5	606	3.3
Shopping	1,363	8.9	1,589	8.7
Social/Recreation	1,356	8.8	1,612	8.8
Eat meals	907	5.9	902	4.9
Personal business	1,698	11.0	1,670	9.1
Other	1,168	7.6	2,078	11.4
Total	15,384	100.0	18,303	100.0

[1] Includes "return to work": The chi-square statistic associated with the table is 168.2 with 8 degrees of freedom

B. *By employment status*

	Workers				Non-workers			
	SCAG observed		STPG simulated		SCAG observed		STPG simulated	
	Frequency	%	Frequency	%	Frequency	%	Frequency	%
Home	4,244	34.8	4,548	30.9	1,109	34.8	1,331	37.2
Work[1]	2,231	18.3	3,318	22.6	37	1.2	0	0
Work-related	396	3.2	649	4.4	30	0.9	0	0
School	808	6.6	606	4.1	37	1.2	0	0
Shopping	841	6.9	1,018	6.9	522	16.4	571	16.0
Social/Recreation	992	8.2	1,109	7.5	364	11.5	503	14.1
Eat meals	735	6.0	698	4.7	172	5.4	204	5.7
Personal business	1,115	9.1	1,307	8.9	583	18.3	363	10.2
Other	833	6.8	1,474	10.0	335	10.5	604	16.9
Total	12,195	100.0	14,727	100.0	3,189	100.0	3,576	100.0

work, other, and home trips. Work-related, shopping and social/recreation trips are also over-predicted, while school trips are under-predicted in the simulation. In terms of relative frequency, work, other, and work-related trips are over-represented in the STPG simulation.

As noted earlier, work activities tend to be governed by rigid schedules, which is not represented in the current versions of STPG. It is plausible that, because of this, the simulation tended to generate trips for workers which would be in reality impossible due to work schedules. The single most important source of the problem, then, would be the use of a statistical distribution model for work durations and the assumption implied in it that the work duration is a random variable.

The distribution of trip purposes by employment, shown in the second part of Table 6, is consistent with this conjecture. The total number of trips is over-predicted for workers by over 20% (12,195 trips observed vs. 14,727 simulated). The relative frequency of home trips is under-predicted, while those of work and work-related are over-represented for workers. As a result, the simulation generated more complex travel patterns with multi-stop trip chains for workers.

The distribution of the number of trips per person by employment is shown in Table 7. The simulation captures overall tendencies in the observed data; both have a mode of two trips per day, for both workers and non-workers. As suggested above, the simulation in fact has produced more workers with 5 or more trips per day, and less with exactly two trips. Workers have been simulated to have more complex daily travel patterns. The distribution of the number of trips is better represented for non-workers.

Observed and simulated trip length distributions are compared in Figure 1 through Figure 4. Figure 1 and Figure 2 are for home-based trips (whose one end is the home base, as traditionally defined) for workers and non-workers respectively; Figure 3 and Figure 4 are for non-home-based trips (neither of whose ends involves the home base) for workers and non-workers respectively. Although the STPG simulation captures the overall tendencies in trip length distribution, there are noticeable discrepancies. Rather surprisingly, the observed distribution for home-based trips for workers from the sub-sample of the SCAG data set has a mode in the shortest range of 1 to 10 min. The simulated distribution appears more plausible with a mode in the 11-to-20 min. range. Except for non-home-based trips for non-workers, discrepancies between the observed and simulated distributions are more noticeable in the ranges from 1 to 10 min. and 31 to 40 min. For non-home-based trips for non-workers, the discrepancy appears to occur in the range from 21 to 40 min.

The observed trip length distributions of non-home-based trips are roughly exponential with a mode in the shortest 1-to-10 min. range. The simulation approximates the observation well for both workers and non-workers, except for that the observed distributions have thicker tails.

The distribution of travel modes is compared in Table 8. Comparisons are made for home-originated trips vs. non-home-originated trips and for workers vs. non-workers. It is shown that the simulation produced better results for auto-driver and auto-passenger than for public transit and walk/bike; likewise results are better for workers than for non-workers, and results for non-home-

Table 7. Distribution of number of trips per person: Observed vs. simulated.

	SCAG observed		STPG simulated	
	Frequency	%	Frequency	%
Workers				
1	25	0.9	0	0.0
2	898	31.7	416	14.7
3	321	11.3	327	11.5
4	557	19.6	488	17.2
5	305	10.8	462	16.3
6	233	8.2	394	13.9
7	174	6.1	300	10.6
8	117	4.1	187	6.6
9	88	3.1	127	4.5
10	54	1.9	59	2.1
>10	65	2.3	77	2.7
Total	2837	100.0	2837	100.0
Non-workers				
1	4	0.6	2	0.3
2	168	25.3	123	18.6
3	69	10.4	59	8.9
4	120	18.1	106	16.0
5	74	11.2	89	13.4
6	71	10.7	77	11.6
7	37	5.6	74	11.2
8	52	7.8	49	7.4
9	30	4.5	27	4.1
10	17	2.6	20	3.0
>10	21	3.2	37	5.6
Total	663	100.0	663	100.0

originated trips are better than those for home-originated trips. Discrepancies are relatively small in terms of percentage figures. Due to the large sample size, however, the differences are statistically very significant.

In the STPG results, both auto driver and auto passenger are over-represented, while public transit and walk/bike are substantially under-represented. These tendencies are more pronounced for home-originated trips, whose modal split is simulated using the trip-interchange model developed by SCAG. The mode transition matrices for non-home-originated trips are producing better results.

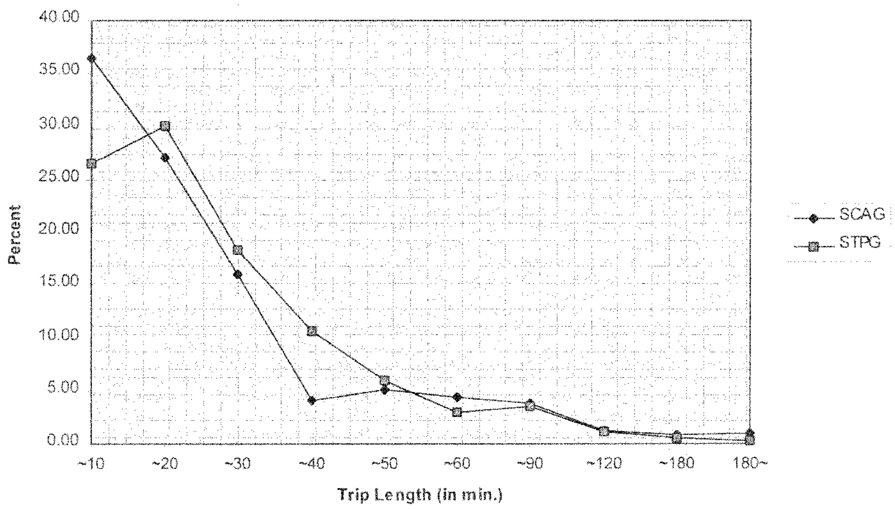

Figure 1. Distribution of home-based trip length for workers.

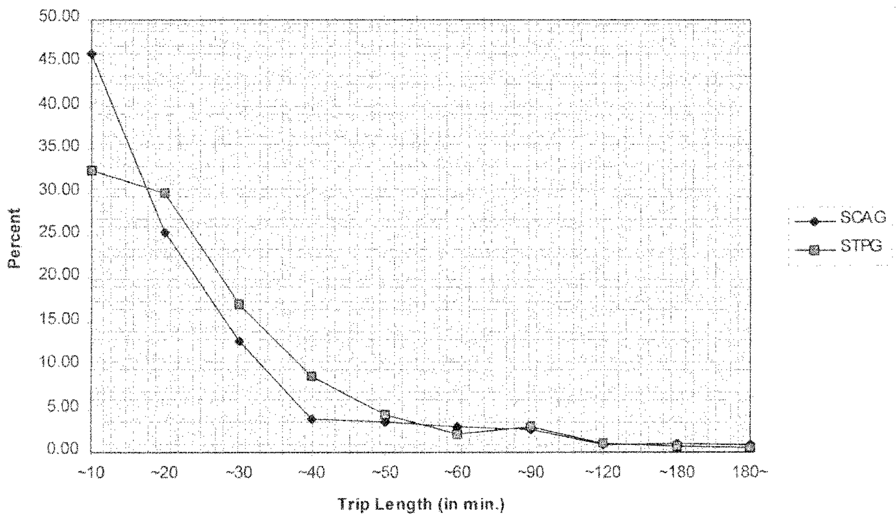

Figure 2. Distribution of home-based trip length for non-workers.

5. Conclusion

This paper has presented an analytical framework for the generation of synthetic activity-travel patterns and demonstrated that daily travel patterns can be created in a practical manner through micro-simulation. The model system proposed in the study performs, in the nomenclature of the conventional

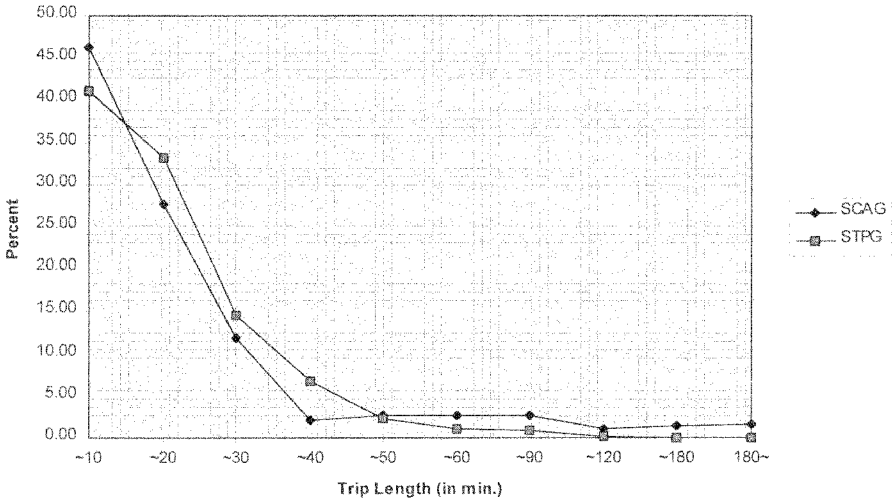

Figure 3. Distribution of non-home-based trip length for workers.

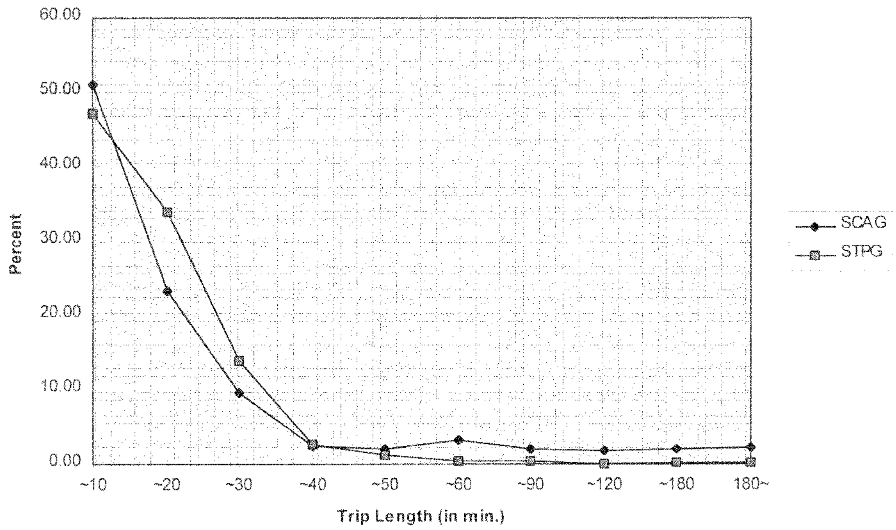

Figure 4. Distribution of non-home-based trip length for non-workers.

demand forecasting analysis, trip generation, trip distribution, and mode choice; namely all of the steps in the four-step procedures except network assignment. Furthermore, unlike the four-step procedures, the proposed system does this for the entire daily travel pattern of an individual and along the time-of-day axis. The system can be a very powerful tool for demand forecasting and policy analysis as well as the generation of synthetic travel pattern data.

Table 8. Distribution of travel modes: Observed vs. simulated.

	SCAG observed		STPG simulated	
	Frequency	%	Frequency	%
All trips				
Auto driver	9,794	63.7	12,383	67.7
Auto passenger	3,733	24.3	5,021	27.4
Public transit	406	2.6	246	1.3
Walk/Bite	1,437	9.4	653	3.6
Total	15,370	100.0	18,303	100.0
Home-originated trips				
Auto driver	3,848	57.2	3,759	64.4
Auto passenger	1,796	26.7	1,916	32.9
Public transit	223	3.3	50	0.9
Walk/Bike	865	12.8	106	1.8
Total	6,732	100.0	5,831	100.0
Non-home-originated trips				
Auto driver	5,946	68.9	8,624	69.1
Auto passenger	1,937	22.4	3,105	24.9
Public transit	183	2.1	196	1.6
Walk/Bike	572	6.6	547	4.4
Total	8,638	100.0	12,472	100.0
For workers				
Auto driver	7,729	63.4	9,759	66.3
Auto passenger	2,956	24.2	4,121	28.0
Public transit	353	2.9	228	1.5
Walk/Bike	1,147	9.4	619	4.2
Total	12,185	100.0	14,727	100.0
For non-workers				
Auto driver	2,065	64.8	2,624	73.4
Auto passenger	777	24.2	900	25.2
Public transit	53	1.7	18	0.5
Walk/Bike	290	9.1	34	1.0
Total	3,185	100.0	3,576	100.0

Excludes 14 observations in the SCAG sample with unknown travel mode. The chi-square statistic associated with the table for all trips is 574.0 with 3 degrees of freedom.

The model system, however, is in its early stages of development, with many research issues to be resolved and model components to be expanded and refined. Issues that have been identified for further investigation include:

- incorporation of fixities in work/school schedules,
- coherent treatment of the work/school base in a series of destination choices,
- integration of mode and destination choices in a series of home-based and non-home-based trips,
- representation of space-time constraints in the activity type, duration and destination choice components,
- representation of pertinent coupling constraints, e.g. a private vehicle must be brought back to the home base, and
- incorporation of accessibility and other measures for increased policy sensitivity.

Some of the weaknesses of the current STPG stems from its history dependent structure. Although this may be resolved by making the model system future dependent, models with future dependencies possess their own difficulties. A promising approach is to establish prisms for each worker first, then apply a two-tier model structure in which activity engagement is first determined for all the prisms, then activities and trips are generated as described here within each prism.

There is no question that a substantial amount of effort should be expended before a reliable and practical model system can be developed. Yet the results obtained so far are extremely encouraging and support the proposed approach as a promising path toward the development of a next generation of transportation planning tools.

Acknowledgments

This study was supported by the Los Alamos National Laboratory through a contract to the Institute of Transportation Studies, University of California at Davis, by the National Science Foundation through a grant to the National Institute of Statistical Sciences for the project “Measurement, Modeling and Prediction for Infrastructural Systems” (DMS 9313013), and the Japanese Ministry of Education, under the Grant-in-Aid for Scientific Research (B)(2) to Kyoto University. The authors are grateful to the Southern California Association of Governments who provided the data used in this study.

Notes

1. Estimation of the types of models involved in the synthetic activity generator presents a range of problems due to (i) potential serial correlation in the error terms, and (ii) inclusion of lagged dependent variables. Although serial correlation alone does not impair consistency in the case of linear models, it does lead to inconsistency in the case of the non-linear models adopted here (see Kitamura 1995 and Kitamura & Bunch 1990, for further discussion). These problems are ignored in the estimation of this study.
2. Mode here refers to the primary mode of a trip. The analysis uses a "linked" trip file where segments of different travel modes within a multi-mode trip are combined into one trip (thus the trip purpose, "change mode," is eliminated) with a primary mode identified.
3. See Kitamura and Chen (1996) for details.
4. These 3,500 individuals are not expected to constitute a hold-out sample as each sample individual may have been in the estimation samples for some modules of the STPG.

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