CHAPTER 17. ACTIVITY-BASED TRAVEL DEMAND ANALYSIS

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17.1 INTRODUCTION

The primary focus of transportation planning, until the past three decades or so, was to meet long-term mobility needs by providing adequate transportation infrastructure supply. In such a supply-oriented planning process, the main role of travel demand models was to predict aggregate travel demand for long-term socio-economic scenarios, transport capacity characteristics, and land-use configurations.

Over the past three decades, however, because of escalating capital costs of new infrastructure, and increasing concerns regarding traffic congestion and air-quality deterioration, the supply-oriented focus of transportation planning has expanded to include the objective of addressing accessibility needs and problems by managing travel demand within the available transportation supply. Consequently, there has been an increasing interest in travel demand management strategies, such as congestion pricing, that attempt to change transport service characteristics to influence individual travel behavior and control aggregate travel demand.

The interest in analyzing the potential of travel demand management policies to manage travel demand, in turn, has led to a shift in the focus of travel demand modeling from the statistical prediction of aggregate-level, long-term, travel demand to understanding disaggregate-level (*i.e.,* individual-level) behavioral responses to short-term demand management policies such as ridesharing incentives, congestion pricing, and employer-based demand management schemes (alternate work schedules, telecommuting, *etc.*). Individuals respond in complex ways to such changes in travel conditions. The limitation of the traditionally used *statistically-oriented* trip-based travel modeling approach in capturing these complex individual responses has resulted in the development of *behaviorally-oriented* activity-based approaches to modeling passenger travel demand.[1]

The origin of the activity-based approach dates back to the 1960's from Chapin's (Chapin 1974) research on activity patterns of urban population. Chapin provided a motivational framework in which societal constraints and inherent individual motivations interact to shape activity participation patterns. This framework, however, ignored the spatial context (or geography of) activity participation and did not address the relationship between activities and travel. During the same time, the first explicit discussion in the literature on activity participation in the context of time and space appears to have been proposed by Hagerstrand (1970).[2] While Hagerstrand's work

[1] The reader will note here that the activity-based approach has emerged in the context of modeling passenger travel demand, not for freight travel modeling.

[2] In his presidential address at a regional science association congress in 1969, Hagerstrand identified three types of constraints that shape individual activity patterns: (1) authoritative constraints, (2) capability constraints, and (3) coupling constraints. Authoritative constraints refer to the constraints imposed by the spatial and temporal opportunities of activity participation (These authoritative space-time constraints laid the foundation for what are now known as "space-time prisms" and "space-time paths"). Capability constraints refer to constraints imposed by biological needs (such as eating and sleeping) and/or resources

addressed the relationship between activity participation and time-space concepts, it was the seminal work by Jones (1979) that explicitly addressed the relationship between activities, travel, and time and space. Specifically, Jones identified travel as derived from the need to participate in activities at different points in space and time. Subsequent to the research of Jones (1979), and a conference held in 1981 on "Travel Demand Analysis: Activity-based and Other New Approaches" (see Carpenter and Jones 1983 for the conference proceedings), the activity-based approach started gaining significant research attention in the 1980s[3].

Parallel to the early research discussed above in the regional science field, microeconomic utility maximization-based consumption and home production theories of time allocation to activities (Becker, 1965; Evans, 1972) further added to the early theoretical foundations of activity-travel analysis. In addition, the random utility maximization-based consumer choice theory (McFadden, 1973) provided the most popular approach to activity-travel analysis to date.

In the 1990s, several factors provided further stimulus to move from the trip-based to activity based approach to modeling travel demand.[4] These factors included: (1) the increased information demands placed on travel demand models by public policy mandates (such as the ISTEA, TEA-21, and the CAAA), (2) the increasing need to evaluate the effectiveness of short-term travel demand management policies (Bhat and Koppelman, 1999), and (3) the increasing realization of the limitations of the trip-based approach from a behavioral validly stand point and a predictive accuracy stand point (see Jones *et al.,* 1990; and Axhausen and Garling 1992). Further, the improved analytical tools, modeling methodologies, computation capacity and power, and data collection methods accelerated the research shift to an activity-based paradigm.

In recent years, activity-based methods have received much attention and seen considerable progress, as discussed in the remainder of this chapter. In the next section (Section 17.2), we discuss the salient aspects of the activity-based approach by presenting a theoretical and policy-oriented comparison of the trip-based and activity-based approaches. Section 17.3 presents an overview of the various activity-travel forecasting systems in the literature. Section 17.4 discusses the emerging developments, and future research directions along three important dimensions of activity participation and travel: (a) Inter-personal interactions, (b) Time, and (c) Space. Section 17.5 focuses on the integration of activity-based travel forecasting systems with other modeling systems (such as land use models and dynamic traffic assignment models) to build larger and comprehensive urban modeling systems. The final section summarizes the chapter.

17.2 Trip-Based Versus Activity-Based Approaches

The fundamental difference between the trip-based and activity-based approaches is that the former approach directly focuses on "trips" without explicit recognition of the motivation or reason for the trips and travel. The activity-based approach, on the other

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(income, availability of cars, *etc.*) to undertake activities. Coupling constraints define where, when, and the duration of planned activities that are to be pursued with other individuals.

[3] For a detailed review of the research on activity-based travel behavior analysis and modeling in the 1980s, the reader is referred to Kitamura, 1988.

[4] For an overview of the research on activity-based travel analysis in the 1990's, the reader is referred to Bhat and Koppelman, 1999.

hand, views travel as a demand derived from the need to pursue activities (see Jones *et al.,* 1990; Bhat and Koppelman, 1999; and Davidson *et al.,* 2007), and focuses on "activity participation behavior". The underlying philosophy is to better understand the behavioral basis for individual decisions regarding participation in activities in certain places at given times (and hence the resulting travel needs). This behavioral basis includes all the factors that influence the why, how, when and where of performed activities and resulting travel. Among these factors are the needs, preferences, prejudices and habits of individuals (and households), the cultural/social norms of the community, and the travel service characteristics of the surrounding environment.

Another difference between the two approaches is in the way travel is represented. The trip-based approach represents travel as a mere collection of "trips". Each trip is considered as independent of other trips, without considering the inter-relationship in the choice attributes (such as time, destination, and mode) of different trips. Such a neglect of the temporal, spatial and modal linkages between the trips can lead to illogical trip chain predictions, and distorted evaluations of the impact of policy actions.[5] On the other hand, the activity-based approach precludes illogical mode-trip chains by using "tours" as the basic elements to represent and model travel patterns. Tours are chains of trips beginning and ending at a same location, say, home or work. The tour-based representation helps maintain the consistency across, and capture the interdependency (and consistency) of the modeled choice attributes among, the trips of the same tour. In addition to the tour-based representation of travel, the activity-based approach focuses on sequences or patterns of activity participation and travel behavior (using the whole day or longer periods of time as the unit of analysis). Such an approach can address travel demand management issues through an examination of how people modify their activity participations (for example, will individuals substitute more out-of-home activities for in-home activities in the evening if they arrived early from work due to a work-schedule change?).

The third major difference between the trip-based and the activity-based approaches is in the way the time dimension of activities and travel is considered. In the trip-based approach, time is reduced to being simply a "cost" of making a trip and a day is viewed as a combination of broadly defined peak and off-peak time periods. On the other hand, activity-based approach views individuals' activity-travel patterns are a result of their time-use decisions within a continuous time domain. Individuals have 24 hours in a day (or multiples of 24 hours for longer periods of time) and decide how to use that time among (or allocate that time to) activities and travel (and with whom) subject to their sociodemographic, spatial, temporal, transportation system, and other contextual constraints. These decisions determine the generation and scheduling of trips. Hence, determining the impact of travel demand management policies on time-use behavior is an important precursor step to assessing the impact of such polices on individual travel behavior.

[5] Take, for example, an individual who drives alone to work and makes a shopping stop on the way back home from work. The mode choices for the home-work and work-home trips in this scenario are not independent. So in the face of transit improvements, the person may not switch to transit because the evening commute shopping stop may be more conveniently pursued by driving. However, the trip-based approach can over-predict the shift to transit due to ignoring the linkage between the trips identified above.

The fourth major difference between the two approaches relates to the level of aggregation. In the trip-based approach, most aspects of travel (number of trips, modal split, etc) are analyzed at an aggregate level. The study area is divided into several spatial units labeled as Traffic Analysis Zones (TAZ). Then, the total numbers of trip exchanges are estimated for each pair of TAZs by each travel mode and by each route, during each coarsely defined time of day. Consequently, trip-based methods accommodate the effect of socio-demographic attributes of households and individuals in a very limited fashion, which limits the ability of the method to evaluate travel impacts of long-term socio-demographic shifts. The activity-based models, on the other hand, have the ability to relatively easily accommodate virtually any number of decision factors related to the socio-demographic characteristics of the individuals who actually make the activity-travel choices, and the travel service characteristics of the surrounding environment. Thus the activity-based models are better equipped to forecast the longer-term changes in travel demand in response to the changes in the socio-demographic composition and the travel environment of urban areas. Further, using activity-based models, the impact of policies can be assessed by predicting individual-level behavioral responses instead of employing trip-based statistical averages that are aggregated over coarsely defined demographic segments.

Given the behavioral basis and conceptual advantages, the activity-based approach can potentially offer a better ability to evaluate a wide variety of transportation policy initiatives that cannot be either analyzed, or may not be accurately analyzed, using a traditional trip-based framework. For example, trip-based models have very limited ability to predict traveler responses to travel demand management strategies such as congestion pricing, because of the highly aggregate treatment of the time-of-day dimension, and the ignorance of temporal linkages across different trips. Activity-based models are better suited to model the impact of congestion pricing strategies because they capture individual responses to tolls including the potential mode shifts, departure timing shifts, and the potential substitution patterns among different dimensions of travel (mode, timing, *etc*). In addition to the incorporation of temporal linkages among various trips (across the day) of an individual, the activity-based modeling approach facilitates the accommodation of the linkages across the activity participation decisions and travel patterns of different individuals in a household. Such an explicit modeling of inter-individual interactions and the resulting joint travel is essential in the context of occupancy-specific tolling strategies such as high occupancy vehicle (HOV) lanes and high occupancy toll (HOT) lanes (Davidson et al., 2007). Trip-based models, on the other hand, have no ability to incorporate joint travel patterns and cannot provide credible estimates of shared-ride travel for informing HOV/HOT lane policy making.

17.3 ACTIVITY-BASED TRAVEL DEMAND MODELING SYSTEMS

This section provides an overview of the activity-based travel forecasting systems in the literature. Most of the models developed to date can be classified into one of two modeling approaches: (1) Utility maximization-based econometric model systems, and (2) Rule-based computational process model systems. However, it is important to note that the above two approaches have been neither exclusive nor exhaustive. Several other approaches, including: (a) Time-space prisms and constraints, (b) operations research/mathematical programming approaches, and (c) Agent-based approaches have been employed, either in combination with the above approaches or separately, to develop activity-based model systems. The modeling approaches and the models within each approach are discussed below.

17.3.1 Utility Maximization-based Econometric Model Systems

The underlying theory behind utility maximization-based modeling systems comes from the economic theories of consumer choice (e.g., Becker 1965) that individuals make their activity-travel decisions to maximize the utility derived from the choices they make. These model systems usually consist of a series of utility maximization-based discrete choice models (i.e., multinomial logit and nested logit models) that are used to predict several components of individuals' activity-travel decisions. In addition to such utility maximization-based model components, several model systems employ other econometric structures, including hazard-based duration structures, and ordered response structures to model various activity-travel decisions. In all, these model systems employ econometric systems of equations (most of which are utility maximization-based) to capture relationships between individual-level socio-demographics and activity-travel environment attributes on the one hand and the observed activity-travel decision outcomes on the other.

The two main criticisms of this approach are that: (1) individuals are not necessarily fully rational utility maximizers (Timmermans *et al.,* 2002), and (2) the approach does not explicitly model the underlying decision processes and behavioral mechanisms that lead to observed activity-travel decisions. Nonetheless, the approach is very amenable to the development of operational activity-based travel forecasting systems. In this section, we provide an overview of a representative sample of such travel forecasting systems that are either fully developed or under development for practical transportation planning purposes. The model systems include:

(1) The models developed (or under development) for various planning agencies such as Portland METRO (Bradley, *et al.,* 1998*)*, San Francisco SFCTA (Bradley, *et al.;* 2001), New York NYMTC (Vovsha, *et al.,* 2002), Columbus MORPC (PB Consult 2005), Sacramento SACOG (Bowman and Bradley, 2005-2006) and Atlanta ARC (PB *et al.,* 2006), and

(2) The models developed in the research community (CEMDAP and FAMOS).[6]

The first group of models can be categorized into (a) *"full individual day pattern"* modeling systems, and (b) *"enhanced (or linked) full individual day pattern"* modeling systems. The *"full individual day pattern"* modeling systems follow the concept of an over-arching daily activity-travel pattern proposed by Bowman and Ben-Akiva (2001). These systems are based on an underlying system of multinomial logit and nested logit models in a particular hierarchy, although with minor variations. The Portland, San Francisco, New York, and Sacramento models belong to this category. We briefly describe the features of the Sacramento model as an example of a *"full individual day pattern"* model in the subsequent section (*i.e.,* Section 17.3.1.1). The *"enhanced (or linked) full individual day pattern"* modeling systems, on the other hand, are an enhancement of the *"full individual day pattern"* models to accommodate intra-household interactions in activity-travel engagement. That is, the full-day activity

[6] For a comparative review of the design features of each of these models, the reader is referred to Bradley and Bowman, 2006.

schedule approach of Bowman and Ben-Akiva (2001) is enhanced to explicitly recognize and model the linkages across the activity-travel patterns of individuals (e.g., joint activity engagement and travel) in a household. The reader is referred to the documentation of the activity-based models developed for Columbus and Atlanta regions (PB Consult 2005, and PB et al., 2006) for details on such linked full individual day pattern model systems.

17.3.1.1 Activity-Travel Forecasting System of the Sacramento Activity-based Model

The activity-travel forecasting system in the Sacramento model, labeled as DaySim, belongs to the *"full individual day pattern"* modeling systems category in that it predicts each individual's full-day activity and travel schedule in the study area.

DaySim consists of an econometric micro-simulation system with a three-tier hierarchy of: (1) Day-level activity pattern choice models (or, simply, pattern-level choice models), (2) Tour-level choice models, and (3) Trip/Stop-level choice models. Each of the models in this hierarchy consists of a series of econometric choice models, as outlined in Table 17.1. For all these individual model components, Table 17.1 lists the model name and the output of the model, the econometric structure, and the set of choice alternatives. As can be observed from the table, each of the activity-travel choices is modeled using either a multinomial logit or a nested logit structure. The reader will note here that the models are numbered hierarchically in the table to represent the sequence in which the activity-travel decisions are modeled in DaySim. The choice outcomes from models higher in the hierarchy (assumed to be of higher priority to the decision-maker) are treated as known in the lower level models.

As can be observed from the table, the pattern-level models consist of models numbered 1.1 (the daily activity pattern model) and 1.2 (the number of tours model). These models predict: (a) the occurrence (and the number) of home-based tours (i.e., tours that originate and end at home) specifically for each of the following seven activity purposes during a day: work, school, escort, personal business, shopping, meal, and social/recreational, and (b) the occurrence of additional stops/trips that may occur (in other tours) for these seven purposes. The tour-level models (numbered 2.1, 2.3, 2.4 and 2.5 in the table) predict the primary destination (i.e., the destination of the primary stop for which this tour is made), travel mode, time-of-day of travel (i.e., time of arrival at, and time of departure from primary destination), and the number of additional stops by purpose (other than the primary stop) for all tours. Tour-level models also include a work-based tour (i.e., a tour that originates and ends at work) generation model (numbered 2.2) that predicts the number (and purpose) of work-based tours for each home-based work tour predicted by models 1.1 and 1.2. The stop-level models predict the stop location (or destination), mode choice, and time-of-day of travel for each of the stops (other than the primary stops) generated in the previous steps.

Among the models listed in Table 17.1, models 1.1, 1.2, 2.2, and 2.5 together form the activity and travel *generation models*, which provide as outputs a list of all the activities, tours, and trips generated for the person-day. These activities, tours, and trips are scheduled using the other tour-level and trip-level models, which can also be labeled as the *scheduling models*. The scheduling models determine the when (time-of-day), where (destination), and how (mode) of the generated activities and travel.

Table 17.1 Activity-Travel Forecasting System of the Sacramento Activity-based Model

Model ID	Model Name and Outcome	Model Structure	Choice Alternatives
Day-level activity-pattern choice models: Predict the number of home-based tours a person undertakes during a day for seven purposes, and the occurrence of additional stops during the day for the same seven purposes. Purposes: work, school, escort, personal business, shopping, meal, and social/recreational, in that order of priority			
1.1	Daily activity pattern model: Jointly predicts whether or not a person participates in tours and extra stops for 7 activity purposes in a day	MNL (Multinomial logit)	Feasible alternatives of 2080 combinations of 0 or 1+ tours, and 0 or 1+ stops for 7 activity purposes. Base alterative is "Stay at home"
1.2	Number of tours for each of the 7 activity purposes for which tour making is predicted from the above model	MNL	1,2, or 3 tours for each purpose
Tour-level models: Predict primary destination, mode and time-of-day, in that order, for all tours. A Work-based tour generation model is also included.			
2.1	Parcel-level tour primary **destination** zone and parcel choice model (for each of the tours predicted in the above step). This model is applied for all tours in the order of their priority, with high priority tour-outcomes known at the low-priority tour models.	NL (Nested logit) for work-tour, and MNL for non-work and non-school tours	Sample of available parcels (parcel availability based on purpose-specific size and travel time). Work-tour model has usual work location in a nest
2.2	Work-based tour generation model: Predicts the number and purpose of work-based sub tours that originate for each home-based work tour predicted by models 1.1, 1.2, and 2.1. These work-based subtours take priority after home-based work tours	MNL model, applied repeatedly	1 (more) subtour for any of 7 purposes, or No (more) subtours. In application, the model is repeated until the 3rd subtour purpose or "No(more) subtour" is predicted
2.3	Tour-level main **mode** choice models (by purpose, for all tours): Predicts the tour-level mode choice	NL	Drive-transit-walk, Walk-transit-drive, Walk-transit-walk, School bus, Shared ride 3+, Shared ride2, Drive alone, Bike, Walk
2.4	Tour-level **time-of-day** choice models by purpose: Predict half-hour time periods of arrival at and departure from primary destination	MNL	Combinations of all feasible half-hour intervals of arrival and departure = 48x49/2
2.5	Intermediate stop generation models (predicts the exact number and purpose of stops for the half-tours leading to and from the primary destination of the tour)	MNL model, applied repeatedly for all half-tours	1 (more) stop for any of 7 purposes, or No (more) stops. In application, model is repeated until the 5th stop purpose or No(more) stops is predicted
Stop-level models (Stops in half-tour before primary destination are modeled in the reverse chronological order. Location, mode, and 30-minute time period of arrival at location are modeled in that order, and departure time is derived from level-of-service tables. After the trip chain for the first half-tour is modeled, the trip chain for the second half-tour back to the tour origin is similarly modeled in regular chronological order)			
3.1	Intermediate stop **location:** Predicts the destination zone and parcel of each intermediate stop, conditional on tour origin and primary destination, and location of previous stops.	MNL	Sample of available parcels drawn from an importance sampling procedure at three levels of geography (stratum, TAZ, and parcel). Parcel availability based on purpose-specific size and travel time.
3.2	Trip **mode** choice (conditional on main tour mode, the mode of previously modeled adjacent trip, and the specific OD pair anchors)	MNL	Drive to transit, walk to transit, School bus, Shared ride 3+ and 2, Drive alone, Bike, Walk
3.3	Trip **time-of-day** choice models by purpose: Predict arrival time (departure time) choice for stops in first (second) half tour, conditional on the time windows remaining from previous choices	MNL	Feasible alternatives among the 48 half-hour time period alternatives

The above-described activity-travel forecasting system is applied, in succession, to each (and every) individual in the study area to obtain the full-day activity and travel information of all individuals in the population.

17.3.1.2 CEMDAP

CEMDAP (Comprehensive Econometric Microsimulator for Activity-Travel Patterns; Bhat *et al.,* 2004; and Pinjari *et al.,* 2006) is a continuous time activity-travel forecasting system that is based on a range of discrete choice, hazard-based duration, and regression-based econometric models. Similar to the afore-mentioned model systems, the activity-travel patterns in CEMDAP are represented in a hierarchy of pattern-level attributes, tour-level attributes, and stop-level attributes. The difference, however, is that the attributes in CEMDAP characterize a continuous time activity-travel pattern built within the space-time constraints imposed by work and school activities. Hence separate representation frameworks and modeling sequences are adopted for workers (defined as adults who go to work or school, and children who go to school on the day) and non-workers (non-working adults and non-school going children), while incorporating coupling dependencies due to inter-personal interactions (between parents and children).

Activity-Travel Representation Frameworks for Workers in CEMDAP (drawn from Bhat and Singh, 2000): The daily pattern of workers is characterized by five different sub patterns: (a) Before-Work (BW) pattern, which represents the activity-travel undertaken before leaving home to work; (b) Home-Work commute (HW) pattern, which represents the activity-travel pursued during the home-to-work commute; (c) Work-based (WB) pattern, which includes all activity and travel undertaken from work; (d) Work-Home commute (WH) pattern, which represents the activity-travel pursued during the work-to-home commute; and (e) The post home arrival pattern (referred to as After-Work or AW pattern), which comprises the activity and travel behavior of individuals after arriving home at the end of the work-to-home commute. Within each of the BW, WB and AW patterns, there might be several tours. A tour is a circuit that begins and ends at home for the BW and AW patterns and is a circuit that begins and ends at work for WB pattern. Further, each tour within the BW, WB and AW patterns may comprise several activity stops. Similarly, the HW and WH commute patterns may also comprise several activity stops. Figure 17.1 provides a diagrammatic representation of the worker activity-travel pattern in terms of the overall pattern, the component tours and stops.

The characterization of the complete workday activity-travel pattern is accomplished by identifying a number of different attributes within the representation discussed above. These attributes may be classified based on the level of representation they are associated with: that is, whether they are associated with a pattern, a tour, or a stop. Pattern-level attributes include the number of tours for the BW, WB and AW patterns, and the home-stay duration before the HW commute pattern. Tour-level attributes include the travel mode, number of stops, and home-stay duration before each tour in the BW and AW patterns, work-stay duration before each tour in the WB pattern, and the sequence of tours in each pattern. Stop-level attributes include activity type, travel time from previous stop, location of stop, activity duration, and the sequence of the stop in the tour.

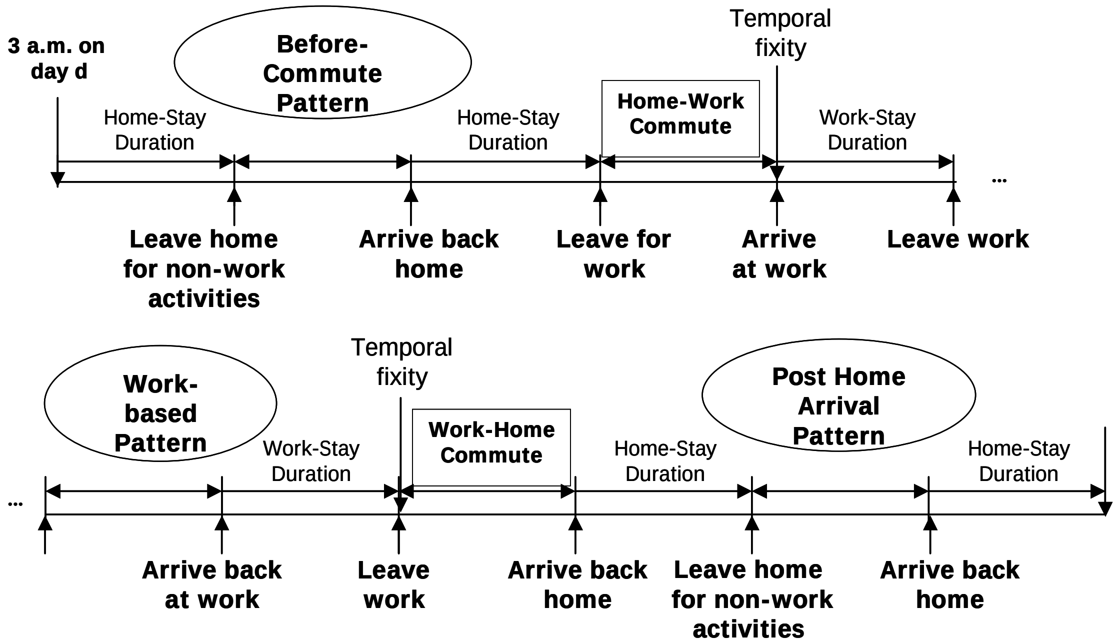


Figure 17.1. Diagrammatic representation of worker activity-travel pattern in CEMDAP

Activity-Travel Representation Frameworks for Non-Workers in CEMDAP (drawn from Bhat and Misra, 2000): In the case of non-workers, the activity-travel pattern is considered as a set of out-of-home activity episodes (or stops) of different types interspersed with in-home activity stays. The chain of stops between two in-home activity episodes is referred to as a tour. The pattern is represented diagrammatically in Figure 17.2. A non-worker's daily activity-travel pattern is characterized again by attributes associated with the entire daily pattern, a tour in the day, and a stop. Pattern-level attributes include whether or not the individual makes any stops during the day, the number of stops of each activity type if the individual leaves home during the day, and the sequencing of all episodes (both stops and in-home episodes). The only tour-level attribute is the travel mode for the tour. Stop-level attributes include the activity duration, travel time to stop from previous episode (except for the first home-stay episode), and the location of out-of-home episodes (*i.e.*, stops).

The modeling of the activity-travel pattern of individuals entails the determination of each of the attributes that characterize the representation structure described above. Due to the large number of attributes and the large number of possible choice alternatives for each attribute, the joint modeling of all these attributes is infeasible. Consequently, a modeling framework that is feasible to implement from a practical standpoint is required. The framework adopted in CEMDAP is described below.

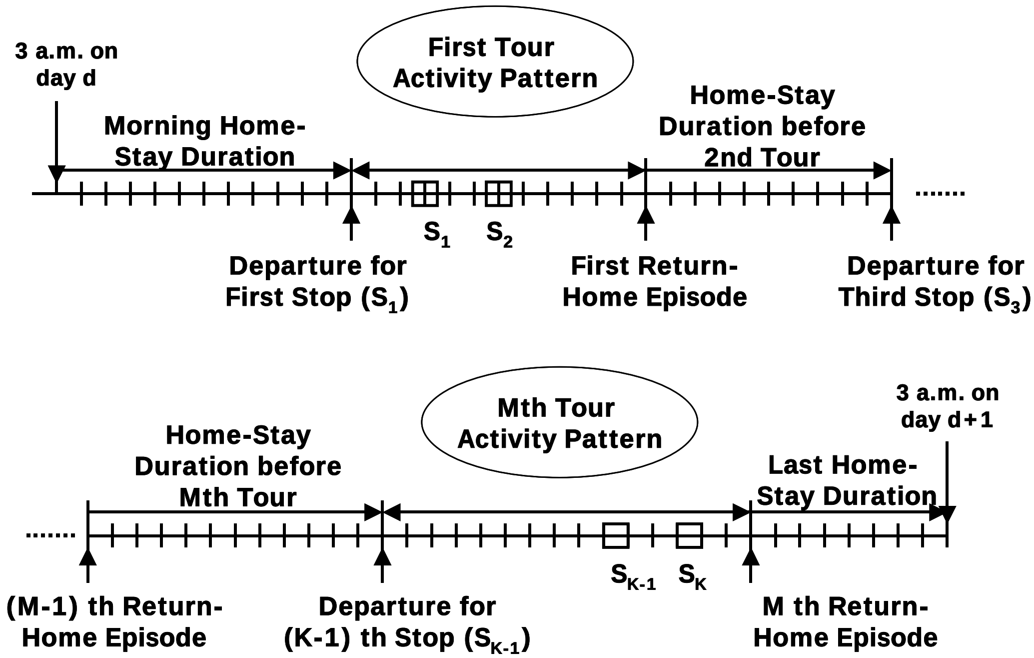


Figure 17.2. Diagrammatic representation of the activity-travel pattern of non-workers in CEMDAP

CEMDAP'S Modeling and Micro-simulation Framework (drawn from Pinjari et al., 2006): CEMDAP comprises a suite of econometric models, each model corresponding to the determination of one or more activity/travel choices of an individual or household. These models may be broadly grouped into two systems: (1) The generation-allocation model system and (2) The scheduling model system. The first system of models is focused on modeling the decision of individuals/households to undertake different types of activities (such as work, school, shopping, and discretionary) during the day and the allocation of responsibilities among individuals (for example, determination of which parent would escort the child to and from school). Table 17.2 lists the precise econometric structure and the choice alternatives for each of the model components in this system. The second system (*i.e.*, the scheduling model system) determines how the generated activities are scheduled to form the complete activity-travel pattern for each individual in the household, accommodating the space-time constraints imposed by work, school, and escort of children activities. That is, these models determine the choices such as number of tours, mode and number of stops for each tour, and the activity-type, location, and duration for each stop in each tour. Table 17.3 lists the econometric structures and the set of choice alternatives for each model in this second system.

Table 27.2 The Generation-Allocation Model System in CEMDAP

Model ID	Model Name	Econometric Structure	Choice Alternatives	Comments
GA1	Children's decision to go to school	Binary logit	Yes, No	Applicable only to children who are students. The determination of whether or not a child is a student is made in the CEMSELTS module (see Eluru *et al*. 2008)
GA2	Children's school start time (time from 3 AM)	Hazard-duration	Continuous time	
GA3	Children's school end time (time from school start time)	Hazard-duration	Continuous time	
GA4	Decision to go to work	Binary logit	Yes, No	Applicable only to individuals above the age of 16 and who are workers. The determination of whether or not an individual is a worker is made in the CEMSELTS module
GA5	Work start and end times	Multinomial logit	528 discrete time period combinations	
GA6	Decision to undertake work related activities	Binary logit	Yes, No	
GA7	Adult's decision to go to school	Binary logit	Yes, No	Applicable only to adults who are students, as determined in CEMSELTS
GA8	Adult's school start time (time from 3 AM)	Regression	Continuous time	
GA9	Adult's school end time (time from school start time)	Regression	Continuous time	
GA10	Mode to school for children	Multinomial logit	Driven by parent, Driven by other, School bus, Walk/bike	Applicable only to children who go to school
GA11	Mode from school for children	Multinomial logit	Driven by parent, Driven by other, School bus, Walk/bike	
GA12	Allocation of drop off episode to parent	Binary logit	Father, Mother	Applicable only to non-single parent household with children who go to school
GA13	Allocation of pick up episode to parent	Binary logit	Father, Mother	
GA14	Decision of child to undertake discretionary activity jointly with parent	Binary logit	Yes, No	Second model in this row is applicable only to non-single parent households with children who go to school
GA15	Allocation of the joint discretionary episodes to one of the parents	Binary logit	Father, Mother	
GA16	Decision of child to undertake independent discretionary activity	Binary logit	Yes, No	
GA17	Decision of household to undertake grocery shopping	Binary logit	Yes, No	Second model in this row is applicable only if the household is determined (using the first model in this row) to undertake shopping
GA18	Decision of an adult to undertake grocery shopping	Binary logit	Yes, No	
GA19	Decision of an adult to undertake household/personal business	Binary logit	Yes, No	
GA20	Decision of an adult to undertake social/recreational activities	Binary logit	Yes, No	
GA21	Decision of an adult to undertake eat out activities	Binary logit	Yes, No	
GA22	Decision of an adult to undertake other serve passenger activities	Binary logit	Yes, No	

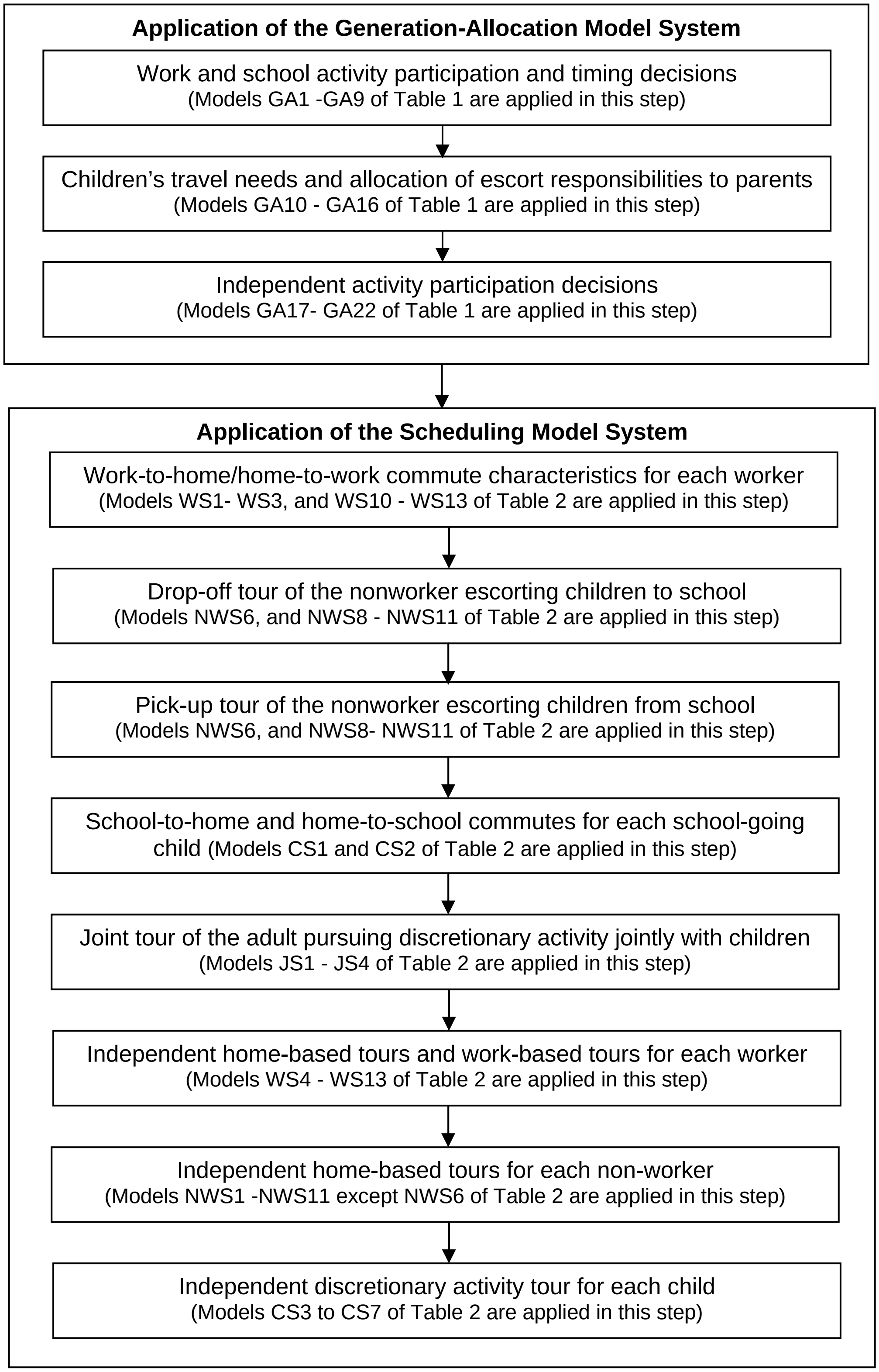
General Notes:
(1) A child is an individual whose age is less than 16 years, and an adult is an individual whose age is 16 years or more.
(2) CEMSELTS = Comprehensive Econometric Microsimulator for SocioEconomics, Land-use, and Transportation Systems.
(3) In the CEMDAP architecture, all individuals in the population have to be classified into one of the following three categories: (1) student (2) worker, and (3) non-student, non-worker. CEMDAP, in its current form, does not accept the category of "student and worker".
(4) GA1- GA9 model the work/school participation decisions, GA10-GA16 model the children's travel needs and allocation of escort responsibility, and GA17-GA22 model the individual-level activity participation choice.

Table17.3 The Scheduling Model System in CEMDAP

Model ID	Model Name	Econometric Structure	Choice Alternatives
WS1	Commute mode	Multinomial logit	Solo driver, Driver with passenger, Passenger, Transit, Walk/Bike
WS2	Number of stops in work-home commute	Ordered probit	0,1,2
WS3	Number of stops in home- work commute	Ordered probit	0,1,2
WS4	Number of after-work tours	Ordered probit	0,1,2
WS5	Number of work-based tours	Ordered probit	0,1,2
WS6	Number of before-work tours	Ordered probit	0,1
WS7	Tour mode	Multinomial logit	Solo driver, Driver with passenger, Passenger, Transit, Walk/Bike
WS8	Number of stops in a tour	Ordered probit	1,2,3,4,5
WS9	Home/work stay duration before a tour	Regression	Continuous time
WS10	Activity type at stop	Multinomial logit	Work-related, Shopping, Household/personal business, Eat out, Other serve passenger
WS11	Activity duration at stop	Linear Regression	Continuous time
WS12	Travel time to stop	Linear Regression	Continuous time
WS13	Stop location	Spatial location choice	Choice alternatives based on estimated travel time
NWS1	Number of independent tours	Ordered probit	1,2,3,4
NWS2	Decision to undertake an independent tour before pickup-up/joint discretionary	Binary logit	Yes, No
NWS3	Decision to undertake an independent tour after pickup-up/ joint discretionary	Binary logit	Yes, No
NWS4	Tour Mode	Multinomial logit	Solo driver, Driver with passenger, Passenger, Transit, Walk/Bike
NWS5	Number of stops in a tour	Ordered probit	1,2,3,4,5
NWS6	Number of stops following a pick-up/drop-off stop in a tour	Ordered probit	0,1
NWS7	Home stay duration before a tour	Regression	Continuous time
NWS8	Activity type at stop	Multinomial logit	Work-related, Shopping, Household/personal business, Eat out, Other serve passenger
NWS9	Activity duration at stop	Linear Regression	Continuous time
NWS10	Travel time to stop	Linear Regression	Continuous time
NWS11	Stop location	Spatial location choice	Choice alternatives based on estimated travel time
JS1	Departure time from home	Regression	Continuous time
JS2	Activity duration at stop	Regression	Continuous time
JS3	Travel time to stop	Regression	Continuous time
JS4	Location of stop	Spatial location choice	Continuous time
CS1	School-home commute time	Regression	Continuous time
CS2	Home-school commute time	Regression	Continuous time
CS3	Mode for independent discretionary tour	Multinomial logit	Drive by other, Walk/Bike
CS4	Departure time from home for independent discretionary tour	Regression	Continuous time
CS5	Activity duration at independent discretionary stop	Regression	Continuous time
CS6	Travel time to independent discretionary stop	Regression	Continuous time
CS7	Location of independent discretionary	Spatial location choice	Pre-determined subset of zones

CEMDAP's micro-simulation prediction procedure is represented schematically in Figure 17.3. Each step in the figure involves the application of several models in a systematic fashion. This micro-simulation procedure is applied to each and every household and individual of an urban area to predict the overall activity-travel patterns in the area.

Figure 17.3 Microsimulation Framework in CEMDAP



17.3.1.3 FAMOS

FAMOS (Florida Activity Mobility Simulator; Pendyala *et al.,* 2005) is similar to CEMDAP in the explicit recognition of space-time constraints, and the continuous time nature of the modeling system. FAMOS consists of a Prism-Constrained Activity Travel Simulator (PCATS) that simulates the activities and trips undertaken by an individual together with the locations, modes, times, durations and sequence of the activities and travel. The unique feature of this simulator is that Hägerstrand's space-time prisms[7] are utilized to represent and model the spatial and temporal constraints under which individuals undertake activities and trips (hence, the name prism-constrained activity-travel simulator). The boundaries (or frontiers) of these space-time prisms, within which the individual activity travel patterns must take place, are determined by using stochastic frontier models (see Pendyala et al., 2002). Subsequently, the activity-travel patterns are simulated within the boundaries of the space-time prisms.

17.3.2 Rule-Based Computational Process Models

Rule-based computational process models (CPM) have been proposed as another approach to modeling activity-travel behavior. A CPM is basically a computer program implementation of a production system model, which is a set of rules in the form of condition-action (if-then) pairs that specify how a task is solved (Garling *et al.,* 1994). CPM researchers argue that complex human activity-travel behavior may not always be able to be represented as an outcome of utility maximization (Timmermans *et al.,* 2002). Rather, the underlying principle of the CPMs is that individuals use context dependent choice heuristics to make decisions pertaining to activities and travel. These models attempt to mimic how individuals think when building schedules. The model systems can be viewed as an exhaustive set of rules in the form of condition-action pairs to specify how a task is solved.

A limitation of CPMs, however, is that there are still unresolved issues in the development of CPMs that make it difficult to determine the statistical significance of the factors that affect scheduling decisions. Also, most CPMs consider the generation of activity episodes (and one or more attributes of each episode) to be exogenous, and focus only on the scheduling or sequencing of activities. Even for activity scheduling and sequencing, it is difficult to enumerate all the decision rules underlying such a complex process. Nonetheless, this research is valuable in providing insights into activity-travel scheduling processes of individuals that can, at the least, be used to inform the development of operational travel demand models.

The important CPMs in the literature are listed and briefly discussed next.

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[7]Hägerstrand's space-time prism is a conceptual framework to capture spatial and temporal constraints on individual's activity-travel patterns. Space-time prisms can be constructed by considering a three dimensional (3D) space, with a two-dimensional horizontal plane representing the geographical space with different activity locations, and a vertical axis representing the time dimension. Within such a 3D space, the space-time coordinates defined by the spatial and temporal constraints of a person (for example, she/he can leave home no earlier than time t_0 and she/he must be at work no later than t_1) form the vertices of a space-time prism. Between the vertices, given the remaining amount of time (t_1 -t_0), and given a maximum possible speed of travel, the set of all locations (*i.e.,* space-time coordinates) she/he can reach form a space-time prism. Thus, space-time prisms represent the feasible activity-travel space defined by the spatial and temporal constraints.

17.3.2.1 CARLA (Clarke, 1986)

CARLA (for Combinatorial Algorithm for Rescheduling Lists of Activities) was one of the earliest rule-based activity scheduling models, developed by the Oxford University Transport Studies Unit (Clarke, 1986). This model uses an exogenously available activity program (list of activities to be scheduled, durations and timing) to generate all feasible activity pattern changes to proposed policies. The potential changes include retiming of activities, change of travel mode, or change in location. Since there can be a large number of resulting activity sequences, the feasibility of an activity sequence is dependent on a number of pre-defined rules including logical timing and location-related constraints and interpersonal coupling constraints, and personal preferences. Subsequently, combinatorics and heuristics are used to choose one of the feasible activity sequences.

17.3.2.2 STARCHILD (Recker et al., 1986 a; and 1986b)

STARCHILD (for Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions) works in two stages. In the first, pre-travel stage, the individual decides on a planned activity episode schedule based on an exogenously available directory of activities along with the duration, location, and time window for participation. In the second stage, the model identifies feasible alternatives (based on a detailed set of constraints, including timing, location, and household level coupling constraints), and groups the alternatives together into statistically similar categories. Subsequently, a logit model is used to establish pattern choice. Thus, STARCHILD extends the feasible activity pattern generation approach of CARLA by adding a logit choice model of actual choice.[8]

17.3.2.3 SCHEDULER (Garling et al., 1989)

In SCHEDULER, a long term calendar (or a set of prior commitments, activity episodes, durations and timing details) is assumed to be present at the start of any time period. From this long term calendar, a small set of episodes with high priority (priority is defined based on prior commitments, preferences and constraints) are selected to be executed in the short term. The short-term activities are sequenced and their locations are determined based on a “distance-minimizing” heuristic procedure.

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[8] The STARCHILD approach was extended later by Recker (1995), who introduced a mathematical programming (or operations research) approach to model household activity-travel patterns. Specifically, he casted the household activity-travel pattern modeling problem (HAPP) as a network-based routing problem, while accommodating vehicle assignment, ride-sharing, activity assignment and scheduling behaviors as well as available time window constraints. The resulting mathematical formulation is a mixed integer linear program that provides an optimal path of household members through time and space as they complete a prescribed agenda of activities. Recker (2001) further expanded on this approach by accommodating the inter-personal interactions among the resource (vehicle) allocation decisions made by households. More recently, Gan and Recker (2008) extended the approach to the case of household activity rescheduling, while also incorporating the impact of uncertainties associated with activity rescheduling behaviors such as activity cancellation, insertion, and duration adjustment. In the context of the mathematical programming approach, Recker (2001) indicates that the approach provides a powerful analytical framework to model complex intra-household interactions associated with household activity-based travel modeling. However, as identified in Recker et al. (2008), further work is needed, especially related to the estimation of such models, to operationalize the models for practical transportation planning purposes.

17.3.2.4 AMOS (Kitamura et al., 1996)
AMOS (for Activity MObility Simulator) takes an observed daily activity-travel pattern of an individual (baseline pattern), identifies the set of associated constraints based on a set of rules, and synthesizes the possible adaptations (*i.e.,* changes in departure time to work, switch mode, *etc.*) in the individual's activity-travel patterns due to the changes in the activity-travel environment. The adaptation possibilities are generated and prioritized in a response generator that is calibrated using neural networks and the stated responses of commuters to a variety of transport policies. Subsequently, an activity-travel pattern modifier identifies the most likely activity-travel pattern response option, and an evaluation routine serves to decide if the option is satisfactory. These adaptation steps are repeated until an acceptable adjustment (in the activity-travel patterns) is found.

17.3.2.5 SMASH (Ettema et al., 1993)
SMASH (for Simulation Model of Activity Scheduling Heuristics) assumes that the activity scheduling process is a sequential and step-wise process of decision making. Starting with an empty schedule (and a long-term activity calendar), at each step, depending on the current schedule and the available alternatives, the individual is assumed to adjust the existing schedule by adding, or deleting, or rescheduling, or simply stopping the adjustment (and hence the scheduling) process. To make a decision on adding, deleting, rescheduling, or stopping the scheduling process, a model calibrated using the nested logit approach is used.

17.3.2.6 ALBATROSS (Arentze and Timmermans 2000, 2005)
ALBATROSS (for A learning-BAsed TRansportation Oriented Simulation System) is a comprehensive and advanced CPM-based activity-travel modeling system developed at the Eindhoven University in The Netherlands. The inputs to the system are (a) an activity diary describing the individuals' activity sequence, purpose, timing and duration, (b) a list of constraints, (c) individual and household characteristics, (d) zonal data, and (e) transport system characteristics. The system uses the activity diary data to start with an initial skeleton-schedule (along with the start times and locations) of fixed activities of the day. Flexible activities are then added to the skeleton. At this point the activity participation profile (activity, with whom, and duration) is known. Subsequently, a scheduling engine determines the timing, trip chaining patterns, mode choice and destinations. The scheduling engine may reschedule the previously scheduled flexible activities whenever a new flexible activity is scheduled.

A distinct feature of ALBATROSS, different from other rule-based models, is the use of observed data to endogenously derive decision-making heuristics, instead of using relatively *ad hoc* rules. Further, the model incorporates learning mechanisms (see Garling *et al.,* 1994; Arentze and Timmermans 2005; and Joh *et al.,* 2006) in the development of decision-making heuristics.

17.3.2.7 TASHA (Miller and Roorda 2003; and Roorda and Miller, 2005)
TASHA (for Travel and Activity Scheduler for Household Agents) is another state-of-the art activity-travel scheduling model. In TASHA, activity scheduling occurs to carry out *projects*. Projects are defined as a set of coordinated activities performed to achieve a common goal. For example, activities such as shopping for food, preparing meals, and having a dinner with guests are all tied together by a common goal, which is to hold a dinner party (*Miller and Roorda 2003*). For each project, an *agenda* (list) of activity

episodes is generated that can potentially be executed in the context of the project. The model recognizes and incorporates the idea that activity scheduling is a path-dependent process and the final outcome of the scheduling process depends on the order in which decisions are made. Thus the agenda is dynamically augmented with further details (such as add an activity, or delete an activity either because it is executed or canceled) until the project's purpose is fulfilled. Innovative and intuitive concepts such as *activity precedence* and *scheduling conflict resolution* are utilized to inform the development of path dependent (or dynamic) schedule planning and adjustment (or rescheduling) strategies and household-level interdependencies. A specifically tailored survey was conducted to observe the process (rather than outcomes, that are observed in the usual activity-travel surveys) of activity scheduling and inform the development of decision-making rules (see Roorda and Miller 2005; and Doherty *et al.,* 2004).

17.3.3 Agent-based Modeling Systems

The agent-based modeling systems incorporate the complexity of human behavior using "agents" that are *autonomous* and *interactive* in nature (see Odell, 2002). The autonomy and the interactive nature are based on behavioral rules that may evolve over time, with every new *experience*. While the use of behavioral *rules* is similar to the rule-based CPM approach, the agent-based approach allows the agents to learn, modify, and improve their interactions with the environment. Thus, the linkages between the choices made by individuals may evolve over time, as opposed to a fixed, and limited, pattern of linkages that are represented in traditional rule-based CPM models. Although the agent-based modeling approach is becoming increasingly popular in such fields as economics (Dosi *et al.,* 1996), social sciences (Gilbert and Cont´e 1995) and ecology (Grimm *et al.,* 1999), it is only in the recent past that this approach has been utilized in the activity-travel behavior modeling arena (see Buliung and Kanaroglou, 2007 for a review). Examples of agent-based activity-travel model systems include ALBATROSS, TRANSIMS, and MATSIM. The reader will note here that although ALBATROSS was discussed within the context of rule-based CPM models (Section 17.3.2.6), the system is growing to incorporate the features of agent-based modeling approaches such as learning and adaptation (see Arentze and Timmermans 2005; and Joh *et al.,* 2006). TRANSIMS (LANL, 2007) and MATSIM (Balmer *et al.,* 2005; and MATSIM, 2007) represent advanced efforts of agent-based activity-travel scheduling coupled with dynamic traffic flow simulation.

17.4 DIMENSIONS OF ACTIVITY-TRAVEL BEHAVIOR: A RESEARCH SYNTHESIS

In this section, we provide a synthesis of the literature on various dimensions of activity-travel behavior that have received substantial attention in the past decade and/or that have started gaining increasing importance in recent years. These different dimensions include: (1) Interpersonal interactions, (2) The time dimension of activity-travel behavior, and (3) The space dimension of activity-travel behavior. Within each area, we also identify directions for future research.

17.4.1 Interpersonal Interactions

The recognition of the role of inter-individual interactions in travel decisions dates back to the 1970's when Hagerstrand (1970) identified coupling constraints that define the timing, location, and the duration of activities that are pursued with other individuals. Early studies in this area include, for example, Koppelman and Townsend (1987) who analyzed household-level time allocation patterns. Subsequently, several studies (e.g. Pas 1985) further emphasized the need for the explicit recognition of inter-individual interactions in activity-based travel analysis, especially at the household level. Since the turn of the century, there has been an increasing recognition that interpersonal interactions play an important role in shaping individuals' activity-travel patterns (see, for example, Srinivasan and Bhat, 2006). In this section, we focus on three major sources of inter-personal interactions: (a) Household members, (b) Children[9], and (c) Social networks.

17.4.1.1 Intra-household Interactions

Very broadly, household-level interactions in an activity-travel context arise from interrelated decision processes associated with (1) the sharing and allocation of responsibilities (maintenance activities) and resources (vehicles), (2) the facilitation of the activity participation and travel needs of mobility-dependent household members (for example, children, the elderly, and other mobility constrained members), and (3) the joint activity engagement and travel. Recent empirical studies in this area focus on:

1. Activity/task allocation (see, for example, Scott and Kanaroglou, 2002; Ettema *et al.,* 2004; Zhang *et al.,* 2004; Srinivasan and Bhat, 2005);
2. Joint activity-travel engagement (see, for example, Gliebe and Koppelman, 2002; Scott and Kanaroglou, 2002; and Zhang *et al.,* 2004); and
3. Children's activity-travel arrangements (Sener and Bhat, 2007)

There are several research challenges remaining in the area of intra-household interactions. These include a better understanding of activity and vehicle allocation among members of a household, and the negotiation and altruistic processes among individuals leading up to observed activity-travel patterns. Such research efforts can be facilitated through the collection of data on task and resource allocation, and joint activity-travel engagement. Another important research need relates to the understanding of the impacts of children and other mobility-dependent individuals on adult activity-travel patterns (and the reverse impact of these adults' patterns on the activity-travel patterns of mobility-dependent individuals). The next section provides a detailed discussion on the importance of explicitly recognizing children and their activity-travel patterns in travel demand modeling.

17.4.1.2 Children's Activity-Travel Behavior

The focus of analysis in existing activity-based research has almost exclusively been on the activity-travel patterns of adults. However, children's travel needs affect the travel patterns of other family members to a considerable extent. Children depend, to a large extent, on household adults or other adults to drive them to after-school activities. In addition to serve-passenger activities, children can also impact adults' activity-travel patterns in the form of joint activity participation in such activities as shopping, going to the park, and other social-recreational activities. In addition, the consideration of children's activity-travel patterns is important in its own right. Specifically, children's activity-travel patterns contribute directly to travel by non-drive alone modes of

[9] Although children are household members, we have listed them a separate category to emphasize the importance of considering children as a major source of inter-personal interactions.

transportation. Thus, it is important to consider the activity-travel patterns of children, and explicitly inter-link these with those of adults' activity-travel patterns.

Most previous research in the area of children's activity-travel patterns has been exploratory in nature (see, for example, McDonald, 2006; and Copperman and Bhat, 2007). The studies that go beyond broad descriptive research have almost exclusively focused on the mode for children's trips to and from school. Only a few studies have begun to address joint travel between parents and children, but even these studies have limited their analysis to accompaniment decisions related to school travel (see Yarlagadda and Srinivasan, 2007). Future research should focus on addressing the factors that contribute to children's non-school mode choice, as well as the activity generation and scheduling decisions related to children's participation in activities during the weekday and weekend. In addition, joint travel and activity participation should address joint participations and accompaniment arrangement for children's non-school activities (see Sener and Bhat, 2007 for a study that addresses who children spend time with in out-of-home recreational activities).

17.4.1.3 Role of Social Networks

A recently emerging research area related to inter-personal interactions is the influence of social networks on activity-travel behavior (Axhausen, 2005, Hackney, 2005; Dugundgi and Walker, 2005; Carasco and Miller, 2006; Arentze and Timmermans, 2007; and Páez and Scott, 2007). The social network of an individual can influence several aspects of his/her activity-travel decisions, including the activity-travel generation, timing and scheduling of activities and trips, and route and destination choices (Arentze and Timmermans, 2007; and Páez and Scott, 2007). Further, understanding the dynamics of social networks (*i.e.,* the formation of new social links and dissolution of old social links) can help forecast the dynamics of activity-travel patterns across time (Arentze and Timmermans, 2007). Besides, incorporating the role of social networks will add to the behavioral realism of activity-travel behavior models. Finally, and interestingly, a particular advantage of considering social networks lies in the decrease in computational time in the destination choice step due to the potential winnowing down of the number of feasible spatial location alternatives for activity participation (Hackney, 2005).

Although only recently emerging, the topic of social networks and its interactions with activity-travel behavior is likely to gain research attention in the coming years. The most limiting issue in the study of social networks today is the lack of information on the extent and nature of social networks in travel behavior survey data (Axhausen, 2006). Hence, the immediate research need is to design and administer surveys with an objective to capture social networks and their roles.

17.4.2 The Time Dimension of Activity-Travel Behavior

The appropriate treatment of the time dimension of activity-travel behavior is perhaps the most important prerequisite to accurately forecasting activity-travel patterns. This is because time is the main backdrop/setting within which the entire activity-travel decision-making takes place (see Kurani and Lee-Gosselin, 1996). Because of the treatment of time as a building block for activity-travel patterns, the following temporal aspects of activity-travel behavior have received significant attention: (1) Time-use in activities, and (2) Activity-travel timing and scheduling.

17.4.2.1 Time-use in activities

The subject of activity time use has gained substantial attention in the travel demand field in the past two decades, with several threads of research efforts. From a conceptual/analytical standpoint, several studies use a resource allocation formulation based on classic economic theories of time allocation (Becker 1965; and Evans 1972). Random utility maximization and related microeconomic theory-based approaches have been particularly popular approaches to modeling activity time allocation (see Meloni *et al.,* 2004; Bhat, 2005; and Jara-Diaz *et al.,* 2007, for recent examples).

Recent research in this area has begun to examine time-use in the context of such related dimensions of activity-travel behavior as: (1) inter-personal interdependencies, accompaniment, and the social context (see, for example, Harvey and Taylor, 2000; Gliebe and Koppelman, 2002; Zhang *et al.,* 2004; and Sener and Bhat, 2007), (2) multi-day/weekly time-use behavior (see, for example, Lee and McNally, 2003; and Spissu *et al.,* 2007), (3) substitution patterns between in-home and out-of-home time use (Kuppam and Pendyala, 2001; and Meloni *et al.,* 2004), and (4) the impact of Information and Communications Technology (ICT) on time-use (de Graaff and Rietveld, 2007). A particular emphasis of recent time-use studies has been on discretionary activities, due to the extent of choice exercised in discretionary activities relative to non-discretionary activities.

It is interesting to note that most of the time-use studies focus only on the activity generation aspect of the activity-travel behavior. That is, the time-use studies to date focus on the types of activities undertaken by individuals within a given time frame. These studies ignore the settings (*i.e.,* the spatial, temporal, scheduling, sequencing and accompaniment contexts) within which the activities are carried out (with a few exceptions mentioned above, which examine the accompaniment and social contexts). The field would benefit from integrated analyses of time allocation and activity settings, including the spatial, temporal, scheduling, and sequencing contexts. Other areas for future research in the time-use area include: (1) the analysis of in-home activity time allocation and activity settings using data with detailed in-home activity type classification, and (2) the application of economic theory-based formulations for the empirical analyses of activity time allocation, monetary expenditures, consumption, and travel.

17.4.2.2 Activity-travel Timing and Scheduling

This section provides a discussion of recent research on individuals' activity-travel timing and scheduling behavior. Specifically, the discussion is oriented along three directions along which the research has progressed: (a) Time-of-day forecasting, (2) Activity-travel scheduling, and (3) Time-frame of analysis.

Time-of-day Forecasting: An important objective of transportation planning is to analyze the temporal variations in transportation demand to identify the need for, and evaluate the potential effectiveness of, travel demand management policies (such as time varying congestion pricing) aimed at spreading the peak period travel into the non-peak periods of the day. Such an analysis requires an appropriate incorporation of the impact of time-varying travel level-of-service (LOS) conditions on activity-travel timing decisions. The importance of modeling time-of-day decisions in response to varying level of service conditions has long been recognized now, dating back to Vickrey's (1969) demand-supply equilibrium-based bottleneck formulation of urban traffic congestion, Small's

(1982) discrete choice demand formulation of time-of-day choice with schedule delay considerations, and Arnott, de Palma, and Lindsey (1993) that combine the bottleneck supply-side formulation of Vickrey and the demand-side formulation of Small. Further, most practical travel modeling applications today adopt some type of travel demand and supply (i.e., transportation level-of-service) equilibration process that helps in incorporating the impact of time-varying travel LOS conditions to a certain extent.

It is important to recognize, however, that high resolution (in time) forecasts are required to better understand the impact of time varying level-of-service on activity-travel behavior. The four-step models, because of their aggregate treatment of the time, are not well-equipped to provide such high resolution forecasts. Further, the trip-based methods that are at the core of four-step models ignore the temporal linkages of different trips. Recent developments toward overcoming these limitations include (1) continuous time modeling approaches, and (2) tour based approaches. Continuous time modeling approaches allow the prediction of activity timing decisions and travel departure/arrival timing decisions in the continuous time domain (or as very finely categorized intervals of time domain; *i.e.,* almost continuous time domain) rather than in discrete time periods such as AM/PM peak/off-peak periods. Examples of such applications include Bhat and Steed (2002), and Pinjari *et al.* (2007). These studies use either hazard-based duration or discrete choice modeling approaches to develop continuous time or almost continuous time models. The time of day models developed within the context of the tour-based approach jointly predict the tour departure time from home/work and either the arrival time back home/work or the tour duration. Such tour-based time-of-day models are at the heart of several comprehensive activity-based travel forecasting systems today. Nonetheless, more research is required to appropriately integrate these developments into a demand-supply equilibration framework (see Section 17.5.1.2 for more discussion).

Activity-travel Scheduling: Earlier research in the activity-travel timing area has largely focused on modeling individuals' travel timing (*i.e.,* trip/tour departure and/arrival time) decisions, by using either discrete time or continuous-time approaches. More recently, there has been an increasing recognition that observed activity-travel timing outcomes are a result of an underlying activity scheduling process that involves the planning and execution of activities over time (see Doherty et al., 2002). In view of this recognition, more research is warranted on the scheduling or sequencing of activities using detailed data on activity-travel scheduling (and rescheduling) processes and mechanisms (see, for example, Doherty *et al.,* 2004; and Lee and McNally, 2006 for recent attempts of such surveys).

Time-Frame of Activity-Travel Analysis: Most of the earlier activity-travel behavior studies have focused on a single day as the time period for analysis of activity-travel patterns. Such single day analyses make an implicit assumption of uniformity and behavioral independence in activity processes and decisions from one day to the next. Clearly, there may be substantial day-to-day dependence as well as variation in activity-travel patterns. Further, many activities (such as grocery shopping or recreational pursuits) are likely to have a longer cycle for participation. Thus, single day analyses cannot reflect multi-day shifts in activity-travel patterns in response to policy actions such as workweek compression.

The limitations of single day activity-travel behavior analysis have led to several multi-day and multi-week data collection efforts in the recent past (see, for example, Axhausen *et al.,* 2002). Availability of multi-day and multi-week data has, in turn, resulted in an increasing number of multi-day/multi-week studies (Schlich and Axhausen, 2003; Bhat *et al.,* 2005; Buliung and Roorda 2006; and Spissu *et al.,* 2008) focusing on understanding the temporal rhythms and variations in activity-travel behavior. However, a limited number of studies focus on determining the appropriate time frame of analysis (see, for example, Habib *et al.,* 2008). While these studies provide preliminary evidence that discretionary activity participation may be characterized as being on a weekly rhythm (or perhaps longer time scale), more research is warranted to determine the appropriate time frame for different types of activities. More specifically, it is important to recognize that not all activities may be associated with time cycles of similar length. Another important and related issue is the time horizon of activity-travel planning and scheduling. Specifically, it is important to understand and model the complex interlacing of multiple time horizons that may be associated with the planning, scheduling, and execution of different activities and related travel over time (Doherty et al., 2002).

17.4.3 The Space Dimension of Activity-Travel Behavior

Space in an activity-travel context refers to location choice behavior and the impact of spatial (or location-specific) elements on activity-travel patterns. Current research interests in spatial analysis include: (1) spatial dependencies, (2) spatial representation, and perception, and (3) space-time interactions and constraints.

17.4.3.1 Spatial Dependencies

Spatial dependencies in an activity-travel context refer to the dependence of activity-travel behavior on spatial elements, and hence the variation of activity-travel behavior over space (Fotheringham *et al.,* 2000). Spatial dependence leads to three spatial analytic issues in activity-travel behavior modeling: (1) spatial autocorrelation (*i.e.,* behavioral similarities across spatially proximate individuals and households due to common unobserved spatial elements; see Franzese and Hays, 2007), (2) spatial heterogeneity (variability in the relationships between activity-travel patterns and exogenous determinants over space due to location-specific effects; see Páez, 2007), and (3) spatial heteroskedasticity (variation in the location-specific unobserved factors that affect activity-travel patterns; Páez, 2006). It is important to account for such spatial dependencies to avoid inconsistent parameter estimates.

17.4.3.2 Spatial Representation and Perception

An important space-related issue in the context of activity-based analysis is spatial representation. Since the 1950s, the spatial configuration of a region has been represented in the form of spatial units, known as traffic analysis zones (TAZs), for the purpose of transportation modeling and planning. These TAZs were created for use in the trip-based approach to travel demand modeling. The shift from the trip-based approach to an activity-based approach to travel demand analysis has generally been accompanied by consideration of a finer spatial representation of areal units (such as parcels). Such a move to finer spatial configurations may be advantageous due to the potential improvement in the accuracy of predicted travel patterns obtained from the better representation of the land-use and transportation network. However, a danger of using very fine resolutions of space is that the geographical context of activity-travel decision-making may be lost (see Guo and Bhat, 2007b). Thus, while there seems to be a general consensus that the TAZ system used in trip-based methods is rather coarse and unable to accurately represent such network attributes as access to transit stops, it is not at all clear what the appropriate spatial resolution (and representation) should be to better capture activity-travel choices. Besides, it may be that different resolutions are needed for different types of activity-travel related decisions (for instance, residential choice versus activity location choice) and different demographic population groups.

Another important issue that is related to spatial representation is the Modifiable Area Unit Problem (MAUP). Specifically, MAUP is associated with the sensitivity of spatial analytic results to the way in which the spatial units are defined. (see Guo and Bhat, 2004; and Páez and Scott, 2004). While there have been several studies showing the presence of the MAUP problem in several analytic contexts involving spatial elements, there have not been adequate attempts at controlling for the MAUP issue in activity-travel studies. This naturally leads to the following question: What is the best way to *represent* the spatial configuration and alleviate MAUP and other spatial representation-related problems in activity-based travel demand models? Guo and Bhat (2004) argue that the fundamental reason behind MAUP is the inconsistency between the *representation* of spatial configuration in analytic models and decision makers' *perception* of space, and that if the spatial characteristics are measured and represented in the same way as decision-makers perceive and process spatial information, there would be less concern of MAUP.

A related issue is the scale at which individuals perceive space when making activity-travel decisions, both in terms of decision units (*i.e.,* the scale of the "neighborhood" that is the unit of decision) as well as the extent of the effect of variables that impact the choice of decision unit (for example, do individuals consider crime rates or access to activities within a narrow 1-mile band or 5-mile bands around spatial units?).

In all, in the context of space perception, there has been very little research on understanding people's mental perceptions of the spatial attributes of the environments in which they live, work, and travel to and from. Taxonomies need to be developed for describing how different types of activity-travel decisions depend on individuals' mental representations of space. People generally do not possess complete knowledge of their surroundings, but are able to select (filter) useful spatial information. Examining this spatial cognition is important for understanding how people adapt through changes of their mental representation of static environments and to changes of the environments at different spatial and time scales (see Kitchin and Blades 2002; and Golledge and Garling, 2004 on spatial cognition and learning issues in travel behavior modeling).

17.4.3.3 Space-Time Interactions and Constraints

It is now widely recognized that human activity and travel patterns are undertaken within time-space prisms, which are defined by spatial-temporal interactions that are influenced by transportation system characteristics (Hägerstrand, 1970). Thus these interactions must be incorporated into the analysis of human activity and travel patterns. Further, the nature of time-space interactions is closely tied to spatial cognition and perception (Pendyala et al., 2002). For example, the spatial perception of, and preference for, a certain kind of land-use mix and built environment in residential choice may be based on household desires to relax time constraints through increased accessibility to activities. Possible future lines of enquiry in this area include: (1) the recognition of the types of time-space interactions in an activity-travel context, (2) data collection for understanding time-space interactions, (3) trade-offs between temporal (activity timing and duration) and spatial (spatial location) decisions, (4) impact of information and communication technologies on time-space interactions, (5) variation of the time-space interactions based on activity type, time-of-day, and activity-travel environment characteristics, and (6) variation of the time-space interactions over longer periods of time (weeks, months and years).

In this context, recent developments in space-time geographic information system (GIS) methods (see for example, the 3D GIS approach by Kwan and Lee, 2004; the temporal GIS approach by Shaw and Xin, 2003; and the integrated spatio-temporal approach of Kang and Scott, 2006) offer very useful visualization, computation, and analytical methods. It is expected that these methods will further advance our understanding of human activity-travel behavior in general, and space-time interactions and constraints in particular.

17.5 INTEGRATION WITH OTHER MODELS

This section focuses on the integration of activity-based travel forecasting models with other model systems of interest in urban transportation planning, with the objective of building comprehensive urban modeling systems.

17.5.1 The Need for Integration

Conventional wisdom has long indicated that sociodemographics, land use, and transportation are intricately linked (Mitchell and Rapkin, 1954,). The recognition of the linkages among sociodemographics, land use, and transportation is important for realistic forecasts of travel demand. Conventional methods, however, use aggregate exogenous forecasts of sociodemographics and land use to feed into travel models and, consequently, cannot capture the multitude of interactions that arise over space and time among the different decision makers. The shortcomings of the conventional approach have led researchers to develop approaches that capture sociodemographic, land-use, and travel behavior processes in an integrated manner. Such behavioral approaches emphasize the interactions among population socioeconomic processes, the households' long-term choice behaviors, and the employment, housing, and transportation markets within which individuals and households act (Waddell *et al.,* 2001). From an activity-travel forecasting perspective, these integrated urban modeling systems need to consider several important issues that are outlined in this section.

17.5.1.1 Generation of Disaggregate Sociodemographic Inputs for forecast years

Activity-based travel forecasting systems require highly disaggregate sociodemographics as inputs, including data records of each and every individual and household in the study area. However, it is practically infeasible to collect the information for each and every household and individual in any study area. Hence, disaggregate population generation procedures are used to create synthetic records of each and every individual and household for activity-travel microsimulation purposes (see Bowman, 2005 for reviews of synthetic population generators). However, to be able to forecast the individual activity-travel patterns and aggregate transport demand at a future point in time, activity-based travel demand models require, as inputs, the disaggregate sociodemographics, and the land-use and transportation system characteristics of that point in time. While the above mentioned SPG procedures can generate the disaggregate sociodemographic inputs for the base year (*i.e.,* the year at which the activity-travel prediction starts and for which the aggregate demographic inputs and the survey data are available), other model systems are required to forecast the disaggregate sociodemographics at a future point in time.

Individuals and households evolve through a sociodemographic process over time. As the sociodemographic process unfolds, individuals may move onto different life-cycle stages such as begin/finish schooling, enter/exit the labor market, and change jobs. Similarly, households may decide to own a house as opposed to rent, move to another location, and acquire/dispose off a vehicle. Such sociodemographic processes need to be modeled explicitly to ensure that the distribution of population attributes (personal and household) and that of land-use characteristics are representative at each point of time and are sufficiently detailed to support the activity-travel forecasting models. There have been relatively limited attempts to build models of sociodemographic evolution for the purpose of travel forecasting. Examples in the transportation field include the CEMSELTS system by Bhat and Colleagues (Eluru *et al.,* 2008), DEMOgraphic (Micro) Simulation (DEMOS) system by Sundararajan and Goulias (2003), and the Micro-analytic Integrated Demographic Accounting System (MIDAS) by Goulias and Kitamura, 1996. Examples from the non-transportation field include DYNACAN (Morrison, 1998), and LIFEPATHS (Gribble, 2000).

17.5.1.2 Connecting Long-term and Short-term Choices

Most of the travel demand models treat the longer-term choices concerning the housing (such as residential tenure, housing type, and residential location), vehicle ownership and employment choices (such as enter/exit labor market and employment type) as exogenous inputs. Consequently, the land-use (in and around which the individuals live, work and travel to) is treated as exogenous to travel demand models. In such cases, the possibility that households can adjust with combinations of short- and long-term behavioral responses to land-use and transportation policies is systematically ignored (Waddell, 2001). A significant increase in transport costs, for example, could result in a household adapting with any combination of daily activity and travel pattern changes, vehicle ownership changes, job location changes, and residential location changes.

While most of the travel forecasting models treat the long-term choices and hence the land-use as exogenous to travel behavior, there have been recent attempts to model the longer-term and shorter-term choices in an integrated manner, including OPUS/Urbansim (Waddell *et al.,* 2006), ILUTE (Salivini and Miller, 2005), and ILUMASS (Strauch *et al.,* 2003). There have also been models studying the relationships between individual elements of land-use related choices and travel behavior choices. However, most of these models and model systems are trip-based. That is, although these studies attempt to study the land-use and travel behavior processes in an integrated manner, the travel behavior aspect of these studies is based on a trip-based approach. There have been a few attempts of integrated land-use and activity-travel behavior studies using the activity-based approach to activity-travel analysis (see Ben-Akiva and Bowman, 1998; Pinjari *et al.,* 2007). Also, ILUTE and OPUS are recent prototype based systems of more comprehensive integrated land-use and activity-travel forecasting systems.

17.5.1.3 Demand-supply interactions

The end use of travel forecasting models is, in general, the prediction of traffic flow conditions under alternative sociodemographic, land use, and transportation level-of-service scenarios. The traffic flow conditions, which are usually predicted after a traffic assignment procedure, are a result of the interactions between the individual-level demand for travel, and the travel options and the level-of-service (or the capacity) supplied by the transportation system. It is important to consider such demand-supply interactions for accurate predictions of activity-travel behavior, and the resulting traffic flow conditions. Further, since the travel level-of-service (and hence the available transportation capacity) varies with the temporal variation in travel demand, and the demand for travel is, in-turn, dependent on the transportation level-of-service, the interactions may be time-dependent and hence dynamic in nature. Thus, it is important to consider the dynamics of the interactions between travel demand and the supply of transportation capacity. See Lin *et al.* (2007) for a review of the literature on the integration of transportation demand and supply analysis, and for a development of an integrated activity-based travel forecasting and dynamic traffic assignment modeling system.

Similar to how transportation market processes (*i.e.,* the interactions between individual-level travel demand and the transportation supply) influence the individual-level activity-travel patterns, the housing and labor market processes influence the residential and employment choices of individuals. In fact, individuals act within the context of, and interact with, housing, labor, and transportation markets to make their residential, employment, and activity-travel choices. While the transportation market process may occur over shorter time frames (such as days or weeks), the employment and housing market processes are likely to occur over longer periods of time. That is, in the short-term, the daily activity-travel patterns are directly influenced by the dynamics of the interaction between travel demand and supply, while in the long-term the activity-travel behavior is indirectly affected by the impact of housing and labor market processes on the residential and employment choices, and also on the land-use and transportation system. If the activity-travel behavior of individuals and households is to be captured properly over a longer time frame, the interactions with, and the evolution over time of, all these markets should be explicitly considered, along with the sociodemographic processes and the long-term housing and employment choices.

17.5.2 An Integrated Urban Modeling System

In view of the preceding discussion, travel demand models should be integrated with other models that can forecast, over a multi-year time frame, the sociodemographic processes and the housing and employment market processes. The integrated model system should be able to capture the above discussed supply-demand interactions in the housing, employment, and transportation markets. A conceptual framework of such a system, labeled as the Comprehensive Econometric Microsimulator for Urban Systems (CEMUS), being developed at the University of Texas, is provided in the diagram below.

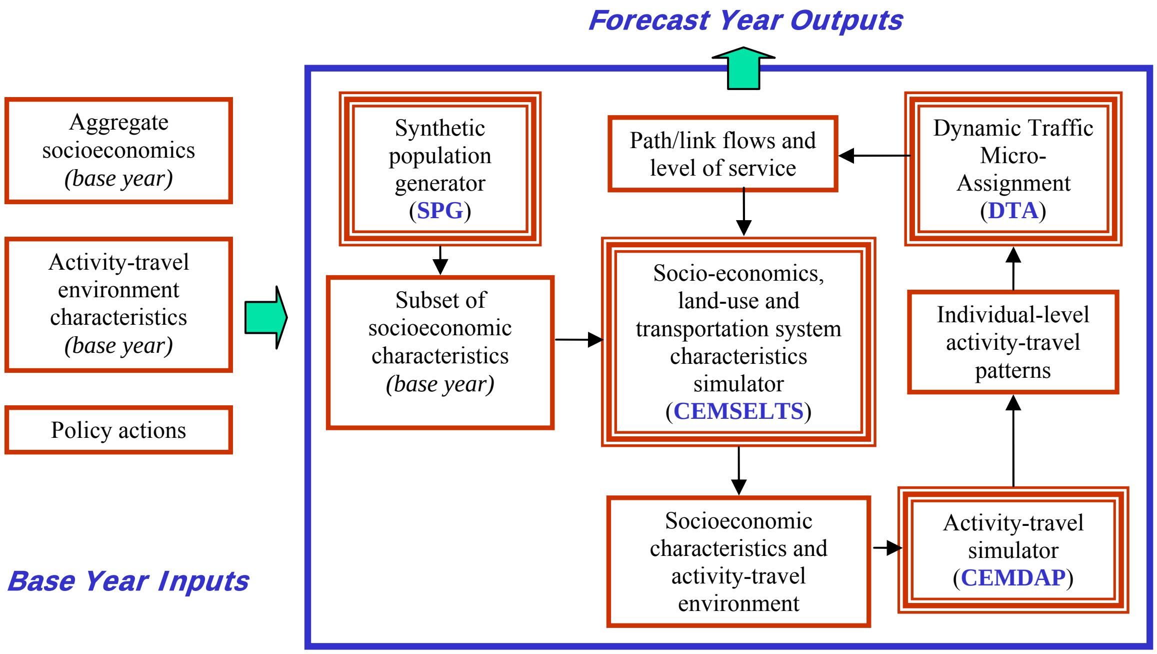

Figure 17.4 Schematic of the CEMUS Model System

CEMUS places the focus on households and individuals, and businesses and developers that are the primary decision makers in an urban system. CEMUS takes as inputs the aggregate socioeconomics and the land-use and transportation system characteristics for the base year, as well as policy actions being considered for future years. The aggregate-level base year socioeconomic data are first fed into a synthetic population generator (SPG) module to produce a disaggregate-level synthetic dataset describing a subset of the socioeconomic characteristics of all the households and individuals residing in the study area (see Guo and Bhat, 2007a for information on the SPG module). Additional base-year socioeconomic attributes related to mobility, schooling, and employment at the individual level, and residential/vehicle ownership choices at the household level, that are difficult to synthesize (or cannot be synthesized) directly from the aggregate socioeconomic data for the base year are simulated by the Comprehensive Econometric Microsimulator for SocioEconomics, Land-use, and Transportation System (CEMSELTS) module. The base year socioeconomic data, along with the land-use and transportation system attributes, are then run through the Comprehensive Econometric Microsimulator for Daily Activity-travel Patterns (CEMDAP) to obtain individual-level activity-travel patterns. The activity-travel patterns are subsequently passed through a dynamic traffic micro-assignment scheme to determine path flows, link flows, and transportation system level-of-service by time of day (see Lin *et al.*, 2007 for a discussion of recent efforts on integrating an activity-travel simulator and a dynamic traffic microsimulator). The resulting transportation system level-of-service characteristics are fed back to CEMSELTS to generate a revised set of activity-travel environment attributes, which is passed through CEMDAP along with the socioeconomic data to generate revised individual activity-travel patterns. This "within-year" iteration is continued until base-year equilibrium is achieved. This completes the simulation for the base year.

The next phase, which takes the population one step forward in time (*i.e*. one year), starts with CEMSELTS updating the population, urban-form, and the land-use markets (note that SPG is used only to generate the disaggregate-level synthetic population for the base-year and is not used beyond the base year). An initial set of transportation system attributes is generated by CEMSELTS for this next time step based on (a) the population, urban form, and land-use markets for the next time step, (b) the transportation system attributes from the previous year in the simulation, and (c) the future year policy scenarios provided as input to CEMUS. The CEMSELTS outputs are then input into CEMDAP, which interfaces with a dynamic micro-assignment scheme in a series of equilibrium iterations for the next time step (just as for the base year) to obtain the "one time step" outputs. The loop continues for several time steps forward until the socioeconomics, land-use, and transportation system path/link flows and transportation system level of service are obtained for the forecast year specified by the analyst. During this iterative process, the effects of the prescribed policy actions can be evaluated based on the simulated network flows and speeds for any intermediate year between the base year and the forecast year.

17.6. SUMMARYAND DISCUSSION

Over the past three decades, the activity-based approach has received significant attention and seen considerable progress. This chapter discusses the fundamentals of the activity-based approach to travel demand modeling, and presents an overview of various activity-based travel forecasting systems. Further, the chapter discusses the recent progress in understanding the time, space, and inter-personal interaction aspects of activity-travel behavior and identifies future research directions. Finally, the chapter emphasizes the need to integrate activity-travel forecasting systems with other systems to design comprehensive and integrated urban modeling systems.

It is worth noting here that several research directions identified in the chapter correspond to understanding the decision-making processes that lead to observed activity-travel patterns. For example, in the context of activity-travel timing outcomes, there has been an increasing recognition that observed activity-travel timing outcomes are a result of an underlying activity scheduling process that involves the planning and execution of activities over time (see Doherty et al., 2002). Similarly, in a spatial context, there is a need to understand individuals' perceptions of space when making activity-travel decisions. Further, in the context of inter-individual interactions, more work is needed to understand the negotiation and altruistic processes among individuals leading up to observed assignment of activity-travel tasks and allocation of vehicles. However, to date, the dominant approach to understanding activity-travel behavior is the analysis of the relationship between exogenous socio-demographics and activity-travel environment characteristics on the one hand, and the revealed activity-travel patterns on the other. This approach does not shed light on the underlying mental processes and behavioral decision-making mechanisms that lead to observed activity-travel patterns. Specifically, we lack a detailed understanding of (1) how households and individuals acquire and assimilate information about their environment, (2) how this information or perception is used to make activity-travel decisions, (3) what aspects of activity travel behavior (and to what extent) are pre-planned (subject to dynamic adjustment and re-adjustment) versus unplanned, (4) the order in which decisions are made, and (5) how individuals interact with other individuals and their activity-travel environment when making activity-travel decisions. One contributing factor for the limited amount of research on decision processes is the lack of detailed data on decision-making mechanisms leading up to the revealed activity-travel patterns. Recent attempts to construct surveys designed to collect information on the activity scheduling process include, for example, Doherty *et al.* (2004), Roorda and Miller (2005), Mohammadian and Doherty (2006), and Lee and McNally (2006). In addition to the need for such detailed data, theoretical developments are needed to understand the decision-making processes that lead up to observed activity-travel patterns. In this context, alternatives to the utility maximization approach, such as lexicographic ordering and satisficing decision-making rules, behavioral theories of bounded rationality, loss sensitivity and subordinateness, variety seeking etc. may need to be explored. A related issue that must be addressed is heterogeneity in decision-making processes across decision-making agents.

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