ACTIVITY BASED TRAVEL FORECASTING[1]

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ABSTRACT

An examination of the theory underlying activity based travel forecasting models, and the classification of the differences among modeling approaches provide a framework which is used to compare six important examples.

Three examples are utility-based econometric systems of equations predicting probabilities of decision outcomes. One is trip-based, a second is tour-based, and the third represents an entire daily schedule. The first two are theoretically inferior but have been validated operationally. The daily schedule system integrates the sequence and timing of activities across tours but has been implemented only as a prototype.

Hybrid simulations use sequential decision rules to predict decision process outcomes. Each example assumes the decisionmaker uses a specific method to simplify a complex decision. The first classifies the alternatives into a small choice set of distinct classes, the second uses a structured search for a satisfactory schedule adjustment, and the third employs a sequential schedule building process. They have challenging data requirements, unvalidated search process assumptions and only partially functional prototypes.

KEYWORDS

activity, pattern, schedule, travel, demand, model, econometric, hybrid simulation, forecast, choice

INTRODUCTION

We present some fundamentals of activity based travel forecasting. If you want to

- become more familiar with the language of activity based modeling,

[1]This paper is the transcript of a tutorial on activity based travel forecasting taught at a conference of the same name in New Orleans, Louisiana, on June 2, 1996. The conference was part of the Travel Model Improvement Program sponsored by the US Department of Transportation and the Environmental Protection Agency.

- understand the concepts underlying the approach,
- compare the alternative approaches,
- or understand important examples, including how well they satisfy the most essential system requirements,

then this presentation is aimed at you.

We'll first look at the motivation for activity based forecasting. Then we'll examine the concepts underlying the methods. We'll identify the basic characteristics of the various modeling approaches, considering the requirements the systems must satisfy, the characteristics they have in common and the fundamental differences between them. Finally, we'll spend a considerable amount of time looking at important examples. We've identified two classes of model systems, which are econometric model systems and hybrid simulation systems. We'll look at three examples in each class, considering how they work, and their particular strengths and weaknesses.

MOTIVATION

Stated simply, the motivation for activity based travel forecasting is that travel **decisions** are activity based.

Concerns about aggregate phenomena such as congestion, emissions and land use patterns lead governments to consider policies aimed at controlling them. These include, for example, employer-based commute programs, single occupant vehicle regulation, road pricing, multimodal facilities and transit oriented land development. But these policies don't affect the aggregate phenomena directly. Instead, thy affect them indirectly through the behavior of individuals. Furthermore, individuals adjust their behavior in complex ways, motivated by a desire to achieve their activity objectives. This idea is illustrated by an example in Figure 1. This figure represents the daily activity and travel pattern of one person who drove alone to work at 7:30 a.m., returned home at 4:40 p.m., and stopped to shop on the way home. In response to an employer sponsored program which gave strong financial incentives to commute by transit, this person made the switch to transit. This required them to begin their commute earlier, at 7:00 a.m., in order to arrive at work on time. Because their preferred shopping destination wasn't on the transit path, they decided to come straight home after work, then drive alone to do their shopping after arriving at home in the evening. This response was rooted in demand for activity, and involved a complex adjustment in their entire day's pattern. In this case, a conventional trip based forecasting model would probably fail to predict the compensating peak period auto trip induced by the transit incentive program. Forecasting models will only be able to accurately capture this kind of response if they represent how people schedule their daily activities.

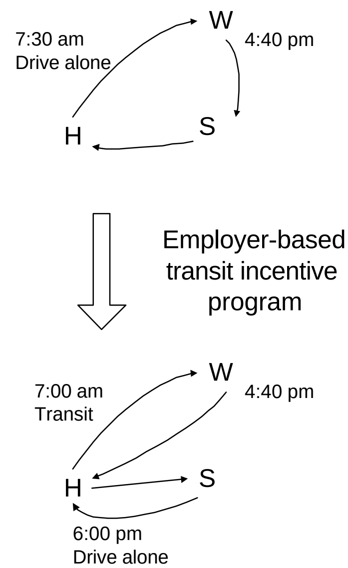


Figure 1. Activity based policy responses involve complex behavioral adjustments motivated by a desire to achieve activity objectives.

A few statistics drawn from a survey of Boston area residents in 1991 reveal some of the complexity and variety in people's activity and travel schedules. Looking first at the number of tours in the daily activity pattern, Figure 2 shows that a substantial percentage of people stay home for the entire day, and 40% take 2 or more tours away from home during the day. The patterns vary dramatically across the population. For example, adults in households with small children are much more likely to take 2 or more tours. Among these, the patterns of males and females differ substantially. Males are less likely to stay home all day and females are more likely to take 3 or more tours.

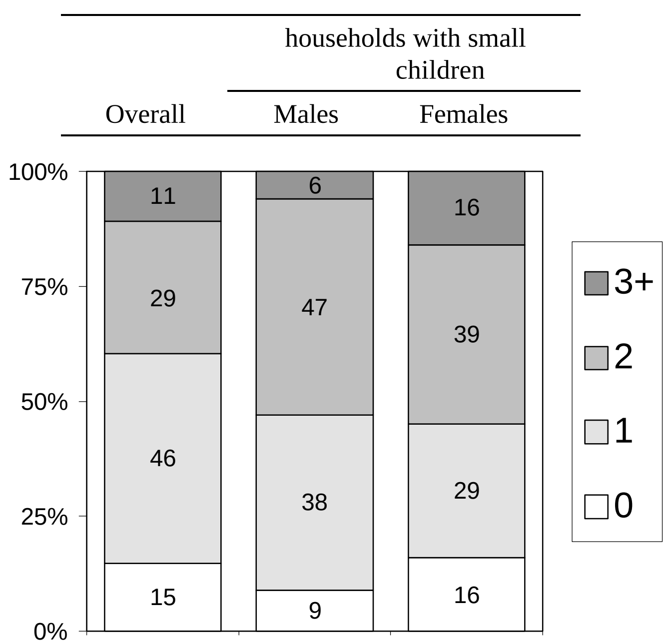


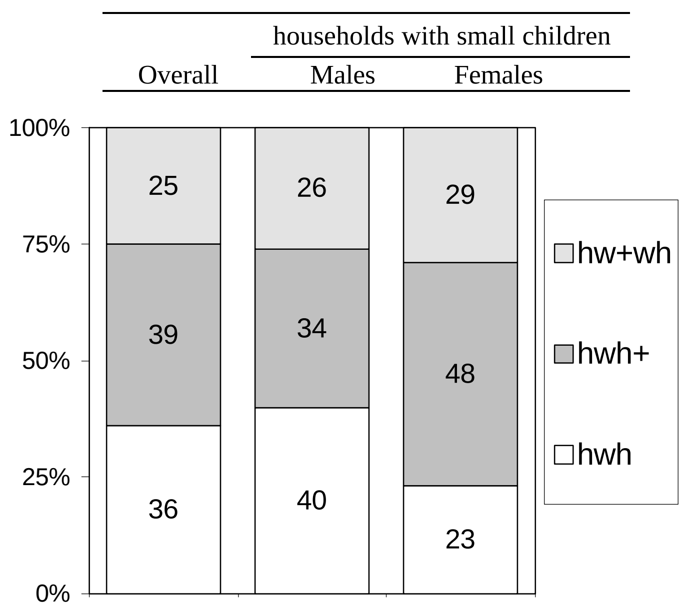
Figure 2: Number of tours in the daily activity pattern (Boston, 1991)

In Table 1 we see that mode choice differs between primary and secondary tours in the day. Drive alone and transit alternatives drop in market share for secondary tours, with substantial increases in shared ride and walk alternatives.

Mode	Primary Tours	Secondary Tours
Drive alone	56%	41%
Shared ride	15	30
Walk	13	26
Transit with walk access	10	2
Transit with auto access	4	0
Bicycle	1	1
Total	100	100

Table 1: Modes of travel on primary and secondary tours.

Looking at the complexity of the work commute tour in Figure 3, we see that 25% of the workers conduct activities away from the workplace sometime in the middle of the workday, and another 39% make stops for other activities on the way to or from work. Here again, the patterns vary within the population. In households with small children, males are more likely than females to travel directly to and from work.



\+ = one or more additional stops

Figure 3: Complexity of the work commute tour.

The distribution of trips by time of day, shown in Figure 4, reveals the bimodal distribution of trips associated with the morning and evening peak periods. Dividing these trips into four categories, it also shows a unimodal distribution for nonworker trips, with substantial amounts of travel occurring during the peak periods. A substantial amount of chained and separate nonwork trips are made by workers, with a heavy skew toward the afternoon and evening hours.

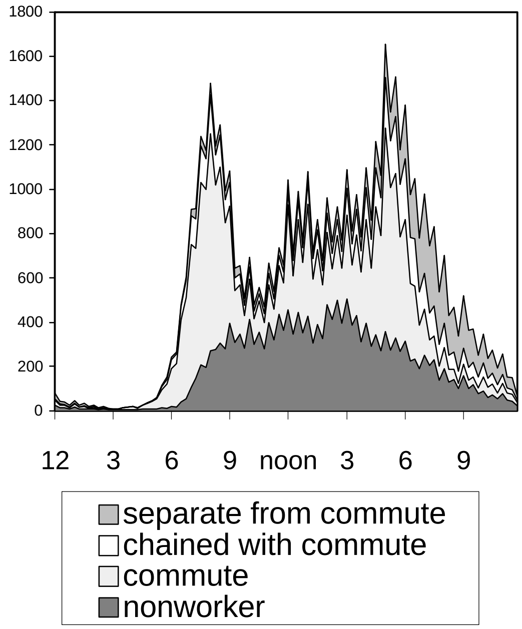


Figure 4: Trips in progress by time of day

The previous statistics reveal the variety of patterns in which travel occurs. But a substantial amount of activities are completed without travel, and many trade-offs are made all the time between travel-based and non-travel alternatives. Many people work at home in ways and amounts that alter their travel patterns. They also make catalog purchases of all types, even for their regular grocery shopping, and use the telephone or computer network to conduct banking or other financial transactions. The point here is that activity based models are needed to capture the trade-offs people make between activity alternatives which involve travel and those which don't.

THE THEORY BEHIND ACTIVITY BASED TRAVEL FORECASTING

Our discussion of the theory underlying activity based travel forecasting starts with the framework in which activity and travel decisions are made. This is followed by an examination of the characteristics of activity and travel demand. Finally we examine theories about the way people make choices, with a focus on methods for dealing with complex decisions.

Activity and travel decision framework

Figure 5 shows how activity and travel scheduling decisions are made in the context of a broader framework, surrounded by and connected in important ways to other decisions (Ben-Akiva and Lerman 1985; Ben-Akiva, Bowman and Gopinath 1996).

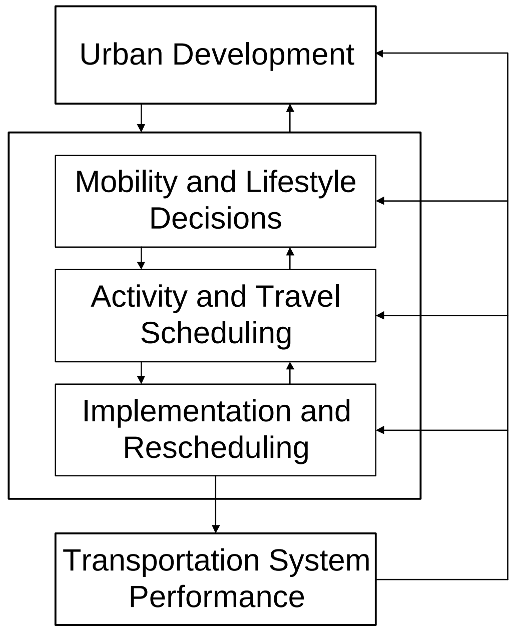


Figure 5: Activity and travel decision framework.

Urban development decisions of governments, real estate developers and other firms influence the opportunities available to households and individuals. Government bodies may provide public transportation services, and tax and regulate the behavior of individuals and firms. Real estate developers provide the locational opportunities for firm and individual location decisions. Firms determine the locations of job opportunities through their location and production decisions.

Household and individual choices, including (1) mobility and lifestyle decisions, (2) activity and travel scheduling, and (3) implementation and rescheduling, fall into distinct timeframes of decisionmaking. Mobility and lifestyle decisions occur at irregular and infrequent intervals, in a timeframe of years. These include major decisions of household composition and roles, workforce participation, workplace, residential location and long term activity commitments. They also include a set of long term transport decisions such as auto ownership, work travel mode, transit and parking arrangements, commute program participation, and, potentially, the acquisition of equipment for automated traveler information systems.

Activity and travel scheduling is a planning function which occurs at more frequent and regular intervals. It involves the selection of a particular set of activities and their priorities, the assignment of the activities to particular members of the household, the sequencing of the activities, and the selection of activity locations, times and methods of required travel. It is convenient to make the simplifying assumption that the activity and travel scheduling decision addresses a particular time span, such as a week or a day. The models we examine later do this, using a 24 hour day as the decision time span.

Within the day, unplanned implementation and rescheduling decisions occur. These include en-route decisions of route choice, travel speed, acceleration, lane changing, merging, following distance, and parking location. Scheduling decisions are made to fill previously unscheduled time with unplanned activities, and rescheduling occurs in response to unexpected events.

Urban development directly influences the decisions of individuals and households, and together the urban development and individual decisions affect the performance of the transportation system. This is manifested in several ways, including travel volumes, speeds, congestion and environmental impact. These manifestations of transportation system performance simultaneously affect the urban development and individual decisions.

The Characteristics of activity and travel demand

One of the most fundamental, well known and widely accepted principles is that travel demand is derived from activity demand. This principle is why the decision framework includes travel decisions as components of a broader activity scheduling decision, and it requires us to model the demand for activities. Chapin (1974) theorized that activity demand is motivated by basic human desires, such as the desires for survival, social encounters and ego gratification. It is also moderated by various factors, including, for example, commitments, capabilities and health. Unfortunately, it is difficult to model the factors underlying activity demand, and little progress has been made to incorporate them in travel demand models. However, a significant amount of research has been done on how household membership moderates activity demand. The conclusions are that (1) households influence activity decisions, (2) the effects differ by household type, size, member relationships, ages and genders, and (3) children, in particular, impose significant demands and constraints on others in the household.

Hagerstrand (1970) focused attention on constraints which limit activity options available to individuals. These include coupling constraints, authority constraints and capability constraints. Coupling constraints require the presence of another person or some other resource in order to participate in the activity opportunity. Examples include participation in joint household activities or in an activity which requires an automobile for access. Authority constraints are institutionally imposed restrictions, such as office or store hours, and regulations such as noise restrictions. Capability constraints are imposed by nature or technology limits. One very important example is the nearly universal human limitation which requires us to return home daily to a home base for rest and personal maintenance. Another example Hagerstrand called the time-space prism; we live in a time-space continuum and can only function in different locations at different points in time by experiencing the time and cost of movement between the locations.

However, not all activity requires our physical movement. Furthermore, the advance of telecommunications technology makes it possible to participate in more and more kinds of activities without physically moving, by increasing the quantity and quality of one- and two-way information exchange which can occur electronically. This leads to choices for individuals between travel and non-travel activity alternatives for work, shopping, conferring and recreation. The modeling implications of this are very important. First, models need to represent the time and space constraints people face. Second, models also need to represent the choices people make between travel and non-travel alternatives.

The choice process and complex decisions

The decision framework, and the factors influencing activity and travel demand give a good picture of the peculiar nature of activity and travel decisions. General theories of how people make choices when faced with complex decisions are also important in the development and critique of alternative modeling approaches.

Every choice has three important elements, including (1) a set of alternatives, (2) a decisionmaker, and (3) a decision protocol, or set of rules. The set of all feasible alternatives is often referred to as the universal set, whereas the set of alternatives which the decisionmaker actually considers is called the choice set. The alternatives in the choice set are defined to be mutually exclusive and collectively exhaustive, so that the decisionmaker must choose one and only one alternative from the choice set.

The alternatives. As we have already seen, the activity and travel scheduling decision is very complex because it involves many dimensions, including activity participation and purpose, priorities, sequence, timing, location, travel mode and route. Within each dimension the number of alternatives can be very large, and sometimes infinite. Viewing the decision as a household decision further complicates the set of alternatives. Thus, in choosing an activity and travel schedule, a decisionmaker faces a very large and complex set of alternatives.

The decisionmaker. Furthermore, the decisionmaker possesses limited resources and capabilities for making this complex decision. Information processing limitations prevent us from being aware of all available alternatives, fully understanding the alternatives we are aware of, and distinguishing similar alternatives. Gathering the information takes time, energy and, often money which are all in limited supply. The result is that decisionmakers act on incomplete information, especially when the choice involves a large, complex alternative set.

The decision protocol. A variety of decision protocols may be employed to make decisions, but all of them can be described in terms of a two-stage process of (1) choice set generation, in which the choice set is selected from the universal set, and (2) choice, in which one alternative is chosen from the choice set. The process can be deliberative or reactive (Rich and Knight 1991; as cited in Ettema, Borgers and Timmermans 1995). In a deliberative process all the alternatives are identified before any are evaluated, and the two stages are conducted sequentially. In a reactive process the evaluation of some alternatives can lead to the identification of additional alternatives, and the two stages are partially completed in an iterative fashion until the choice is finally made.

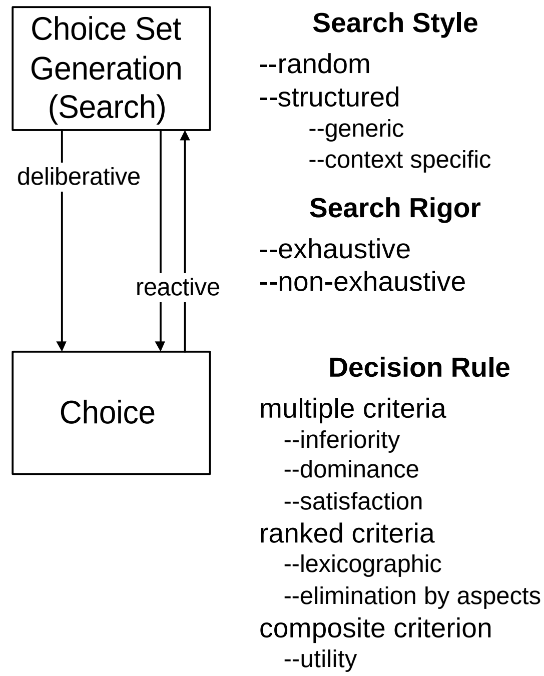


Figure 6: Decision protocols can be viewed as a two stage process of choice set generation, characterized by a particular search style and rigor, followed by choice, characterized by a particular decision rule. The two stages can be conducted sequentially in a deliberative process, or iteratively in a reactive process.

Choice set generation, which can be thought of as a search for alternatives, is characterized by its style and rigor. The search style can either be random, in which no systematic method is employed for finding alternatives, or structured. The structure of a search can be generic or context specific. For example, a search could be structured by an attempt to find alternatives which are similar to the most recently found alternative. A generic structured search might define "similar" generically, whereas in a context specific structured search the definition of "similar" may depend on the nature of the most recently found alternative. An exhaustive search is one which finds all the alternatives before finalizing the choice. A non-exhaustive search stops before all the alternatives have been identified, with one result being that the choice is likely to be suboptimal.

In the choice stage of the decision protocol, the alternatives are judged on one or more criteria, such as travel cost and travel time, and the choice is made by employing a decision rule which is based on the criteria. The choice stage is characterized by its decision rule. Decision rules which employ one or more unranked criteria include inferiority, dominance and satisfaction. An inferiority rule eliminates alternatives which are inferior to another alternative in every criterion. A dominance rule selects alternatives which are superior to every other alternative in every criterion. A satisfaction rule sets a minimum standard for every criterion and selects alternatives which satisfy every minimum standard.

None of the rules which employs multiple unranked criteria is assured of uniquely choosing one and only one alternative. In contrast, rules which employ ranked criteria can arrive at a clearly defined choice. A lexicographic rule applies the dominance rule to the most important criterion. If two or more alternatives dominate all other alternatives, but are equal in the most important criterion, the tie is broken by comparing them on successively less important criteria until only one dominant alternative remains. Elimination by aspects (Tversky 1972) applies the satisfaction rule to the most important criterion, eliminating all alternatives which fail to satisfy. The remaining alternatives are judged on successively less important criteria, eliminating those which don't satisfy at each step, until only one alternative remains.

Finally, the decision rule may involve the use of a composite criterion. Here multiple criteria are transformed into a single scalar criterion by means of a linear or nonlinear combination. The alternative is chosen which best satisfies the composite criterion.

In models of decisions one of the most commonly assumed decision protocols is a deliberative process in which an exhaustive search is followed by a utility maximization choice. The utility function serves as a composite criterion. The use of this decision protocol in models of activity and travel choices is frequently criticized because the large alternative set makes it unrealistic to assume an exhaustive search followed by the rational evaluation of a utility function for every alternative. Several alternative decision protocols have been hypothesized to better represent how individuals cope with complex alternative sets. These include (1)non-exhaustive search, (2) selection based on habit, (3) adaptive decisions, which adjust prior decisions in response to changing conditions, (4) satisfaction rules which stop the search when a satisfying alternative is found, and (5) bounded rational decisions (Simon 1957), in which a non-exhaustive search generates a manageable choice set, to which a utility-based decision rule is applied.

Summary.

We close this section on the theory underlying activity based travel forecasting with a list of the important points:

- Activity and travel scheduling decisions are made in the context of a broader framework which includes urban development decisions of governments, developers and firms, the long range mobility and lifestyle decisions and within day implementation and rescheduling decisions of individuals, and the performance of the transportation system.
- Important characteristics of activity and travel demand include
  - travel demand is derived from activity demand,
  - household membership influences individual decisions, and
  - choices are constrained
    - by a time-space continuum
    - and by capability, coupling and authority constraints.
- Choice theory suggests that
  - decisions can be viewed as a two stage process of choice set generation and choice, and
  - individuals use coping mechanisms in order to make decisions with limited resources when the alternative set is as large and complex as that of the activity and travel scheduling decision.

MODELING APPROACHES

Our examination of theory in the previous section provides the ideas and the concepts for examining the activity based modeling approaches. In this section we build a framework which can be used to understand, compare and evaluate specific modeling approaches which have been attempted. We start by asserting that the heart of the modeling problem is combinatorial, and then present a list of requirements which can be used to judge how well any modeling effort solves the problem. We proceed to characterize the modeling approaches which have been attempted, first in terms of features shared by all the approaches, and then by a classification of the ways in which they differ from each other. In the final sections of this presentation we will use this framework to examine six important examples of attempts to incorporate activity based methods into travel forecasting models.

The fundamental modeling problem

The fundamental problem facing the activity based travel modeler is combinatorial. The challenge is to adequately represent a decision process which has infinitely many feasible outcomes in many dimensions. To show the size of the combinatorial problem, Table 2 lists the dimensions of the activity and travel scheduling decision and provides an estimate of the number of alternatives faced by an individual. Some of the dimensions are continuous, notably timing and location. But if we simplify by transforming these into discrete categories, we get in the neighborhood of 10^{17} alternatives available to the individual.

Number of activities per day	10	10
Sequence		10!
Timing	10 per activity	100
Location	1000 per activity	10,000
Mode	5 per activity	50
Route	10 per activity	100
Total		**10^{17}**

Table 2: An estimate of the number of daily activity schedule alternatives facing an individual

Like the decisionmaker, the modeler must simplify. But unlike the decisionmaker, who can simplify any way he or she pleases, the modeler must simplify in a way which matches the behavior of the decisionmaker. We need a set of requirements with which we can measure how well a model system solves this combinatorial problem.

Model system requirements

Figure 7 lists the requirements which we expect an activity based travel forecasting model system to satisfy. First, it should be theoretically sound, both behaviorally and mathematically. Without these we can not rely on the results. Second, the scope must be complete enough to make the model useful. If important dimensions of the activity scheduling decision are missing, the model prediction will be incomplete and of limited use. Enough resolution of the daily schedule alternatives is required to capture behavior which affects the aggregate phenomena in which we're interested. For example, the resolution of the time dimension must be fine enough to capture time-of-day shifts in response to congestion pricing, and their effects on traffic congestion. The scope of the model must enable it to deal with the relevant policy issues. Third, the resource requirements of the model must allow it to be implemented. In addition to the data we need for estimating the model parameters, we need to validate the model using a different set of data. To use the model for prediction we must also be able to generate reliable forecasts of the exogenous variables used by the model. The model must also be simple enough so that the logic and computation required make it technically and financially feasible to develop, maintain and operate. Finally, the model must produce valid results.

- theoretically sound
    - behaviorally
    - mathematically
- complete scope
    - daily schedule
        - dimensionality
        - resolution
    - flexible policy scope
- practical (resource requirements)
    - data
        - estimation
        - validation
        - operation
    - logic (software)
    - computation (hardware)
- valid results

Figure 7: System requirements for an activity based travel forecasting model system

Commonalities among the various modeling approaches

Let us now consider the characteristics which are common to most of the activity based modeling approaches. First, they all fit into the activity and travel decision framework which we presented in Figure 5, with a focus on the activity and travel decisions. Second, they all represent the decision process as a two-stage decision protocol of choice set generation, or search, followed sequentially or iteratively by the choice itself, as shown in Figure 6.

Third, all the models are disaggregate, representing the behavior of a single decisionmaker. They are intended to generate predictions with disaggregate data, which requires the generation of a representative population. The model is applied to each decisionmaker in the population, yielding for each person either a simulated daily travel itinerary or a set of probabilities for the alternatives in the choice set. The trips in the itinerary can then be aggregated and assigned to the transport network, resulting in a prediction of transport system performance. This process may need to be repeated to achieve statistically reliable predictions.

Although the models require the generation of a disaggregate population, they do not require this to be done a certain way. Various well understood techniques exist for generating a disaggregate population, using data from sources such as the census, household surveys, counts and exogenous forecasts. Examples of these techniques include iterative proportional fitting, of which the Fratar method is a special case, and models of household evolution which may employ transition matrices and choice models.

In summary, the similarities of the various modeling approaches consist of the decision framework, the two-stage choice process and the use of disaggregate methods.

Differences among the various modeling approaches

Despite the similarities, each of the proposed activity based model systems is unique in many ways. We have classified the basic differences along 4 dimensions. As indicated in the introduction, the major classification distinguishes econometric models from hybrid simulation models. We can also classify each model system as representing either household decisions or individual decisions, by its operation as a synthetic model or a switching model, and by whether it predicts probabilities or simulates outcomes.

Econometric vs hybrid simulation models. Econometric and hybrid simulation models use different decision protocols. As shown in Figure 8, econometric models represent the choice set generation, or search, stage very simply, either assuming the decisionmaker considers all feasible alternatives, or using a simple search rule (heuristic) which results in a large choice set. Most of the model is devoted to the complex representation of a utility-based multi-dimensional choice. No iteration occurs between search and choice. Hybrid simulations, on the other hand, focus most of their attention on the choice set generation stage, employing a complex search heuristic which yields a very small choice set. A very simple utility or satisfaction based model is used to represent the choice from this set. Often the protocol involves iteration between search and choice.

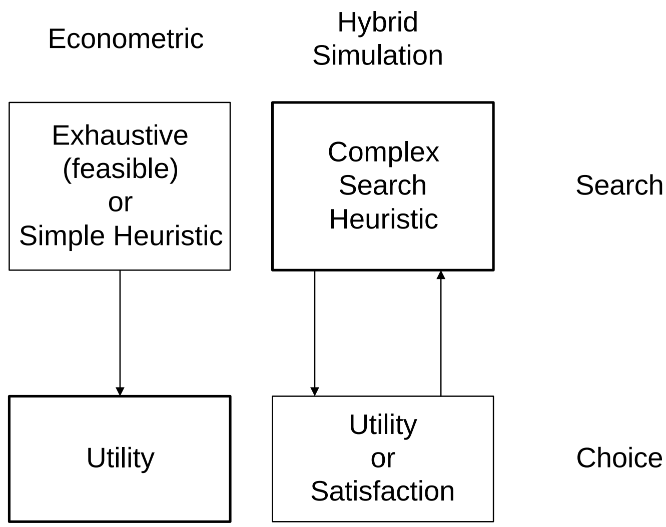


Figure 8: Econometric and hybrid simulation decision protocols. Econometric models represent the search simply, and focus attention on the choice. Hybrid simulations focus on the search, representing the choice simply

Another distinction is that econometric models are systems of equations which predict the probability of decision outcomes. In the case of discrete outcomes, there is one equation per possible outcome. In contrast, hybrid simulations are systems of sequential decision rules which predict decision process outcomes.

Household vs individual decision. The difference between household and individual decision models is straightforward. In an individual model one decision yields one person's schedule of activities and travel. In a household model one decision yields many schedules, one for each person in the household.

Synthetic vs switching models. A synthetic model constructs a person's activity and travel schedule from scratch. A switching model, on the other hand, starts with a given schedule and adjusts it in response to a change in conditions.

Probability vs realization. This difference is based on how the disaggregate outcomes are predicted. When the model is applied to an individual decisionmaker a probability model calculates probabilities of each potential outcome, whereas a realization model predicts the decision. An econometric model is naturally a probability model because it predicts the probabilities of all potential outcomes, but it can also be implemented as a realization model via Monte Carlo simulation, in which one of the potential outcomes is selected in a random draw using the predicted probabilities. Hybrid simulation models, in contrast, can only be implemented as realization models.

ECONOMETRIC MODEL SYSTEMS

We have established a framework in which activity based travel forecasting systems can be understood and compared, by examining the theory of activity based travel, stating the requirements which the forecasting systems should satisfy, identifying the important commonalities among approaches, and classifying the ways in which the systems differ. In the next two sections we look at examples from the two major classes, starting in this section with the econometric model systems.

As we explained already, econometric model systems are systems of equations representing probabilities of decision outcomes. They are based on the theory of probability and statistics, generate probabilities for all alternative outcomes, and are usually based on a utility maximization assumption. Typically, these model systems rely heavily on multinomial logit and nested logit probability models.

Econometric model systems achieve the needed simplification by subdividing decision outcomes and aggregating the alternatives. For example, in the examples which we review, one system subdivides outcomes by modeling decisions about trips instead of the entire daily schedule. All the examples aggregate activity locations into geographic zones.

Developers of econometric model systems attempt to retain behavioral realism by integrating the component models of the system. One method of integration models some dimensions of the scheduling decision conditional upon the outcomes of other dimensions. For example, the choice of travel mode for the work commute is conditioned by the choice of workplace. The second major method of integration accompanies this conditionality, and involves the use of measures of expected utility. It is used when the utility of a conditional choice influences the utility of a conditioning choice. In the previous example, the choice of workplace is influenced by the expected utility of travel arising from all the available commute modes.

Within the class of econometric model systems we have identified three subclasses, based on how they divide the decision outcomes. The simplest and oldest subclass divides the daily schedule into trips. Some more recent models combine trips explicitly in tours. The last subclass combines the tours in a daily schedule. In Figure 9 we compare the three subclasses by seeing how they represent a hypothetical daily schedule. In this schedule the person departed for work at 7:30 A.M., traveling by transit. At noon they walked out for personal business, returning to work at 12:50 P.M. At 4:40 P. M. they returned home from work, again by transit. That evening at 7:00 P.M. they drove to another location for shopping, returning home at 10:00 P.M. The trip-based model represents the schedule as 6 one-way trips. The “direction” of the trips is in terms of trip production and attraction rather than direction of movement. Time is not modeled explicitly. In the tour-based model the trips are explicitly connected in tours, introducing spatial constraints and direction of movement. Finally, the daily schedule model explicitly links the tours and explicitly models the time dimension, although at a coarse resolution. We will look at an example of each of these econometric approaches.

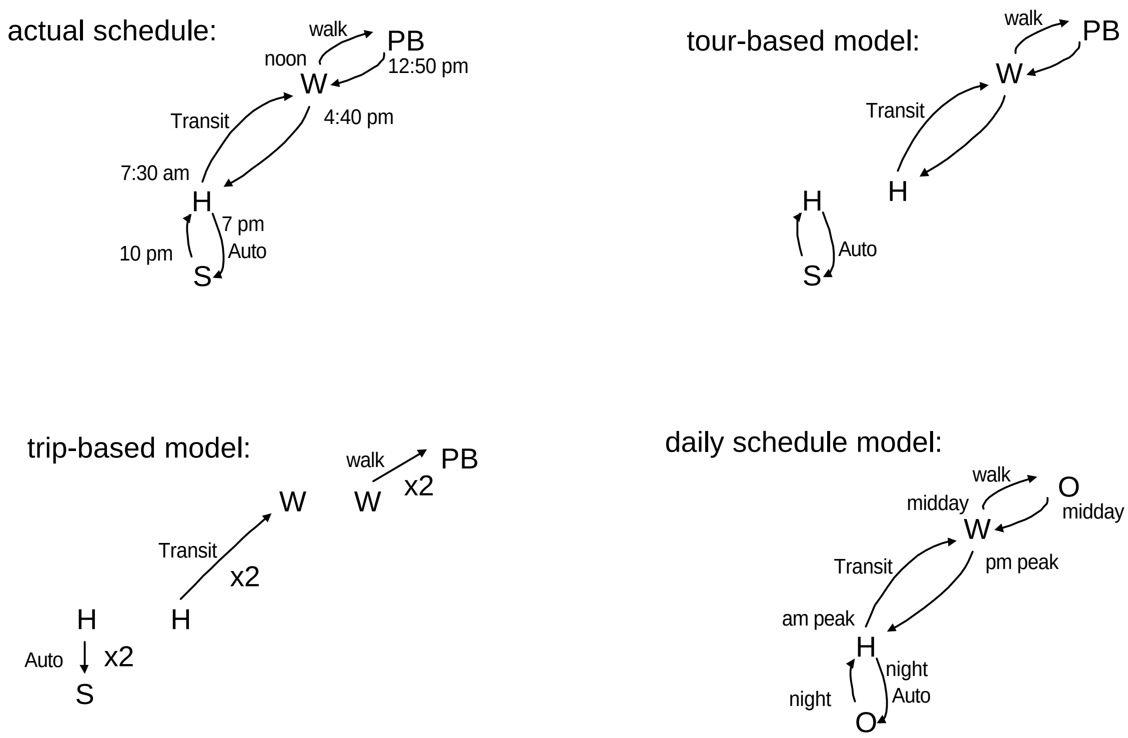


Figure 9: The three subclasses of econometric model systems are characterized by how they subdivide the daily schedule outcome. Trip-based models subdivide the schedule into one-way trips. Tour-based models separate the schedule into tours. Daily schedule models explicitly link the tours.

<u>Trip-based system</u>

The first example of an integrated trip-based econometric model system was developed during the mid 1970's for the MTC in San Francisco (Ruiter and Ben-Akiva 1978). The demand model portion of the MTC system has three major components, as shown in Figure 10(a). The mobility and lifestyle component represents long term decisions related to auto ownership and home-based work trips. Short term activity and travel decisions deal with other home based trips and non-home based trips. Each model component is conditioned by choices at the higher level, and the activity and travel models influence the mobility and lifestyle models via measures of expected utility. Figure 10(b) shows details of the mobility and lifestyle component of the model system. At this level we can see that the system is in the class of household models because it explicitly models work travel decisions for two workers in the household. Arrows in the figure show how the models are integrated, with solid arrows indicating conditionality and dashed arrows indicating expected utility. For example, the number of autos chosen in the auto ownership model is conditioned by the choice of workplace. That is, the model assumes the workplace is known when it models the auto ownership decision. The auto ownership decision itself conditions the mode choice model. The model also accounts for how auto ownership is influenced by the ease of travel for shopping and work by including variables of expected utility generated by the shopping destination and mode choice and work mode choice models.

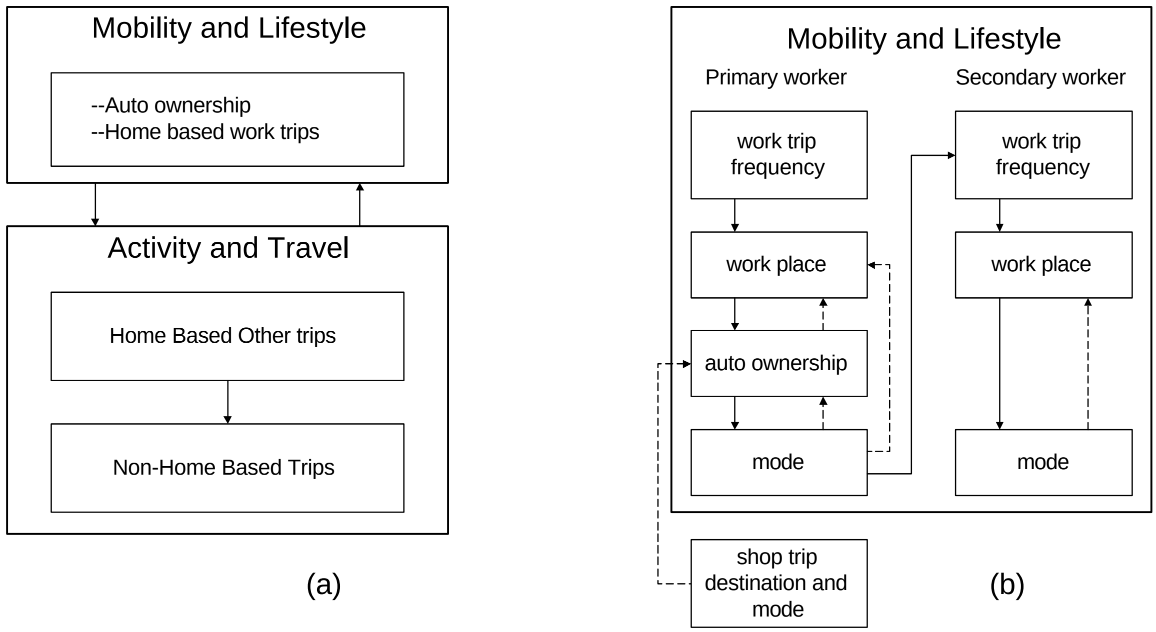


Figure 10: (a) Three major components of the MTC model system, and (b) details of the mobility and lifestyle component, showing integration of the models via conditionality (solid arrows) and expected utility (dashed arrows). (Source: Ruiter and Ben-Akiva 1978)

In summary, key features of the trip-based model systems, exemplified by the MTC system, are their composition of disaggregate choice models and their integration via conditionality and measures of expected utility according to the decision framework. Their key weakness is the sequential modeling of home-based and non-home based trips rather than the explicit representation of tours. The consequence is that the models may not correctly predict scheduling changes which can occur in response to changing conditions.

<u>Tour-based system</u>

Tour-based systems were first developed in the late 1970's and 80's in the Netherlands (Gunn, van der Hoorn and Daly 1987; Daly, van Zwam and van der Valk 1983; Hague Consulting Group 1992), and are being used extensively there and elsewhere in Europe, with the most recent systems being developed in Stockholm, Sweden (Algers et al. 1995) and Salerno, Italy (Cascetta, Nuzzolo and Velardi 1993). Figure 11, which depicts the basic structure of the Stockholm model system, shows how the tours for various purposes are explicitly modeled. Work tour decisions are conditioned by the mobility and lifestyle decisions, and condition all other activity and travel decisions. The model system makes heavy use of expected utility measures, strengthening the connections across dimensions of the activity and travel scheduling decision.

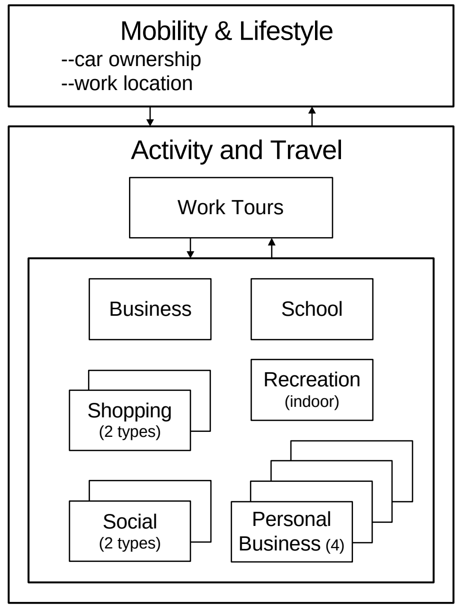


Figure 11: The Stockholm tour-based model system

The work tour decision, Figure 12, is modeled as a nested logit model. It includes the household's decision of who will work today, how the household's autos will be allocated among the workers, and the mode of travel for workers who do not use a household auto.

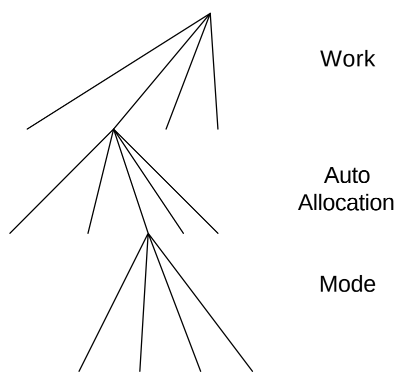


Figure 12: The nested logit work tour model

The model of household shopping tours, Figure 13, conditioned by the work decision, determines how many shopping activities the household will undertake, who will do them, the type of tour on which they will be done, and the mode and destination of the tour. A shopping activity can be assigned to one or more household members, and if it is assigned to a worker, the options exist of conducting the activity on a home-based tour, a work-based tour or chained to the work tour enroute between work and home.

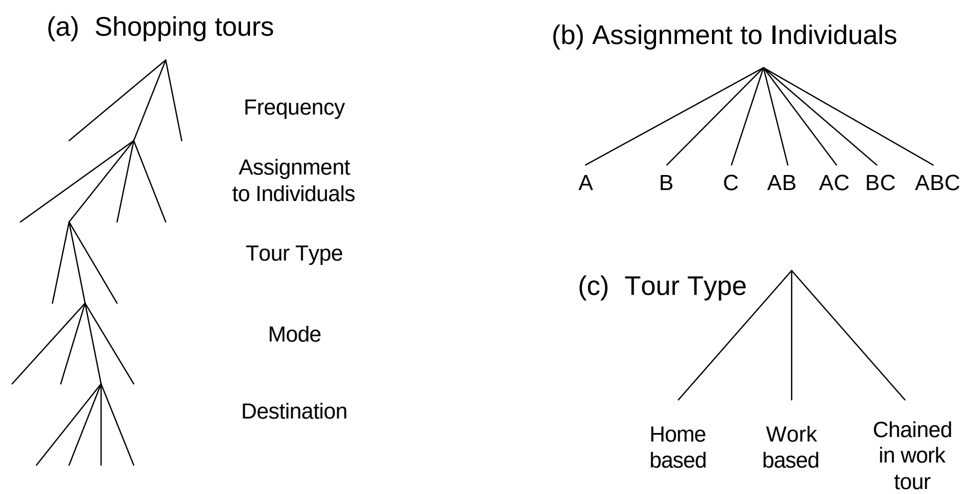


Figure 13: The shopping tours model (a) assigns each shopping activity to one or more household members (b). If a shopping activity is assigned to a worker, the tour type model determines whether the activity occurs on a home-based tour, a work-based tour, or chained in the work tour (c).

Summarizing the tour-based econometric approach, the key feature is the explicit representation of tours, and trip chaining within tours. The Stockholm example also explicitly models household decisions. The key weaknesses of the tour-based systems are that they lack an overarching pattern connecting the day's tours, and they don't integrate the time dimension into the model structure.

Tour-based systems, exemplified by the Stockholm model system, represent the most advanced state of the practice of activity based travel forecasting. These systems have been carefully validated and are being widely applied in Europe. In contrast, the remaining four examples which we will review next, including the daily schedule econometric system and all the hybrid simulations, exist only as prototypes or partially implemented systems.

Daily schedule system

The daily schedule system (Ben-Akiva et al. 1996; Ben-Akiva and Bowman 1995; Bowman 1995) deals directly with the two weaknesses of the tour-based models. First, it explicitly represents the choice of a daily activity pattern, which overarches and ties together tour decisions (Figure 14). Second, it incorporates the time of day decision. The daily activity pattern is characterized as a multidimensional choice of primary activity, primary tour type, and the number and purpose of secondary tours. The model distinguishes between the primary tour of the day and secondary tours. For each tour, it models destinations, times of day and modes.

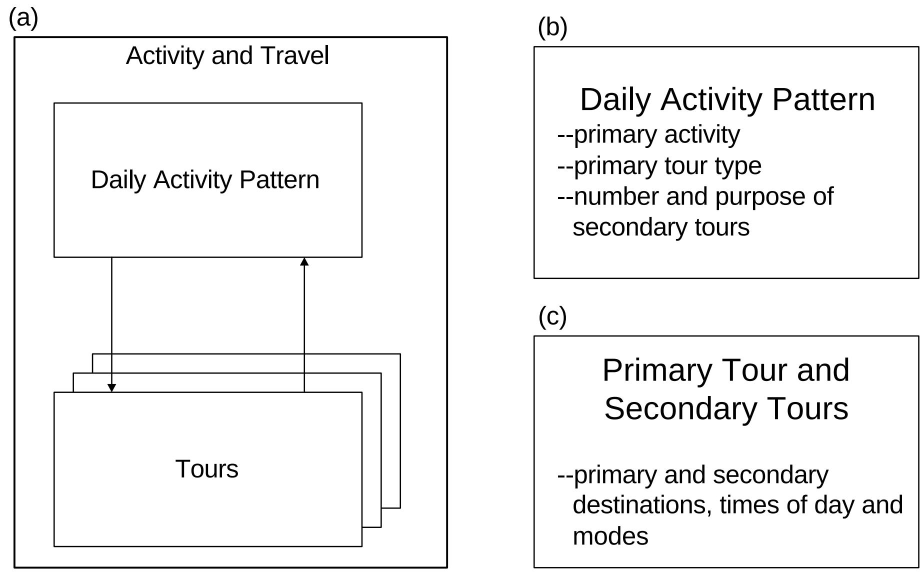


Figure 14: (a) The daily schedule system consists of a daily activity pattern which overarches and ties together the tour decisions. (b) The daily activity pattern and (c) the tour decisions are multidimensional choices.

The model is implemented as a nested logit system, with tour decisions conditioned by the choice of daily activity pattern (Figure 15). They also influence the choice of daily activity pattern through the expected utility mechanism described earlier for the trip and tour-based systems. In the prototype, the daily activity pattern model is a choice among 55 patterns including (1) whether to stay home all day or participate in activities involving travel, and (2) conditional on travel, the choice of a particular pattern. The Boston travel survey, used for the prototype, did not include records of at-home activities. If such data were available, it could be incorporated at this level of the model. The model system design calls for the explicit modeling of secondary destinations on tours, conditional on the choices for the primary destination.

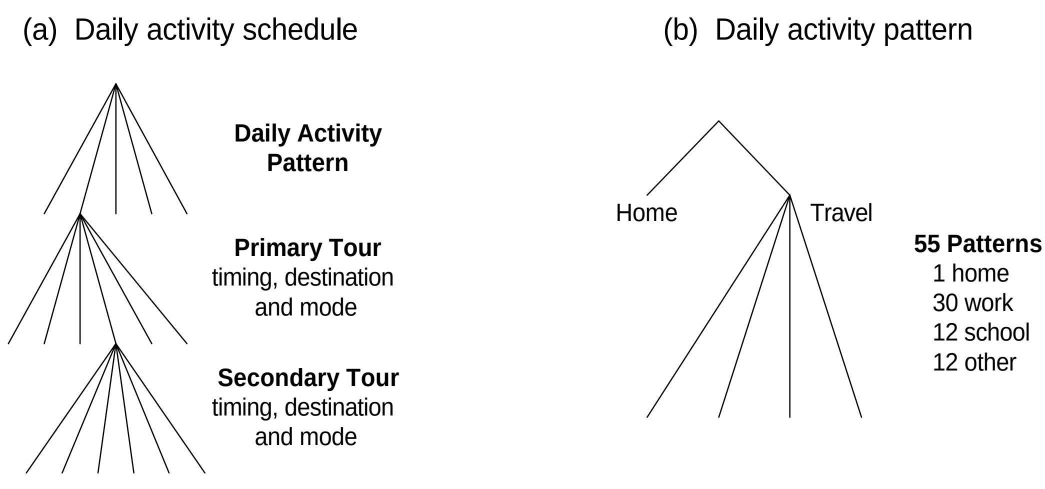


Figure 15: Daily schedule system prototype

The key feature of this system, the integrated daily schedule, is also the source of one of its two main weaknesses. Tying tours together in the daily activity pattern results in a very large choice set which is behaviorally unrealistic and computationally burdensome. Constraints, utilities and probabilities must be computed for literally billions of alternatives. Ironically, the prototype nevertheless suffers from an incomplete representation of the daily schedule; the time of day is aggregated into only 4 time periods, secondary stops on tours are omitted, the time of day linkages are incomplete and household linkages are not explicitly modeled.

HYBRID SIMULATIONS

We have already described hybrid simulations as sequential decision rules predicting decision process outcomes, and noted their focus of attention on choice set generation. These systems are based on various decision theories, such as cognitive limitation or the notion of a search which terminates with acceptance of a satisfying alternative. A simple utility based decision rule is often used in the choice stage of the decision protocol. Hybrid simulations achieve simplification by subdividing the decision process into separate sequential steps. Additionally, all hybrid simulations developed to date achieve simplification by limiting the decision scope, omitting important dimensions of the activity and travel scheduling decision.

A great variety of hybrid simulations is possible, and they are harder to subclassify than the econometric systems. We review three particular model systems which, although they do not characterize the entire class of hybrid simulations, are important examples and demonstrate some of its variety. The STARCHILD system (Recker, McNally and Root 1986b; 1986a) is the earliest example of this class, which models the activity and travel scheduling decision as a classification and choice process. AMOS (RDC Inc. 1995) is a very recent example which has been partially implemented in the Washington, D.C. area, representing the decision as a satisficing adjustment. SMASH (Ettema, Borgers and Timmermans 1993; Ettema et al. 1995) was developed in the Netherlands, and represents the scheduling decision as a sequence of schedule building decisions.

STARCHILD: classification and choice

STARCHILD (Figure 16) starts with a detailed activity program which must be supplied from outside the model. The activity program identifies many details of the schedule, including activity purpose, participation, duration and location, as well as constraints on sequence, timing and coupling of activities. It then models the scheduling decision as a four step process which yields the timing and sequence of the activities in the program. Choice set generation occurs in the first two steps. Feasible alternatives are exhaustively enumerated with careful attention to constraints. They are then classified, using a statistical similarity measure, and one alternative is chosen to represent each of approximately 3-10 classes. The remaining two steps comprise the choice process. A decision rule is used to eliminate some alternatives. In the prototype which was developed, all inferior alternatives were eliminated, according to an intuitive objective criterion. A multinomial logit model then represents a utility maximizing choice among the remaining non-inferior alternatives. The developers of STARCHILD conceived the activity schedule as a plan, which is followed by implementation and rescheduling, but did not develop the latter model.

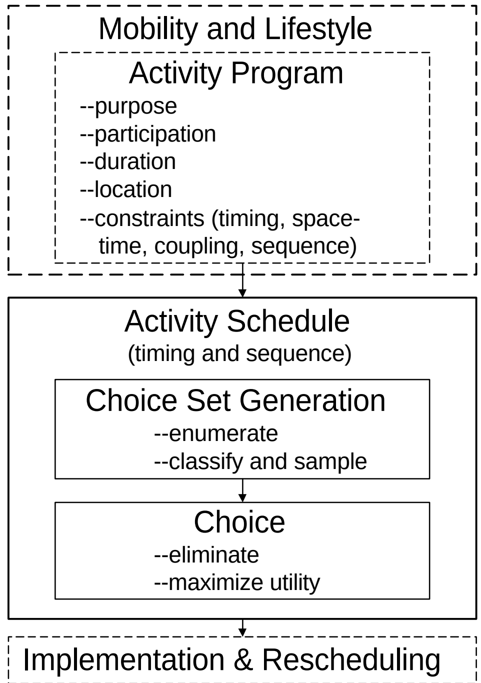


Figure 16: STARCHILD takes an externally supplied activity program and simulates the scheduling decision. Choice set generation involves enumerating, classifying and sampling the schedule alternatives. This is followed by a simple utility maximization choice.

STARCHILD's key features are its detailed representation of constraints in the identification of feasible alternatives, and the use of a classification method to generate the choice set. As a model intended for use in forecasting travel, it has two key weaknesses. First, it relies on external sources to predict important dimensions of the activity and travel schedule, including activity participation, purpose, location and travel mode. Second, the classification and sampling rule may inadequately represent the true choice set. The rule generates a very small choice set with only one alternative of each distinctively different class, whereas people may frequently choose from a small choice set of similar competing alternatives.

AMOS: satisficing adjustment

AMOS (Figure 17) requires as input an even more detailed activity schedule than STARCHILD. This, however, is because AMOS is designed as a switching model. Given a baseline schedule and a policy change, it chooses a basic response, such as a mode change, which limits the domain of search for a feasible adjustment. A structured search rule then completes the choice set generation stage, yielding one feasible adjustment. A simple choice model accepts or rejects the adjustment. If the adjustment is rejected then the structured search is repeated until an acceptable adjustment has been found. If no acceptable alternative is found for the desired basic response, then the process can loop back to the choice of another basic response.

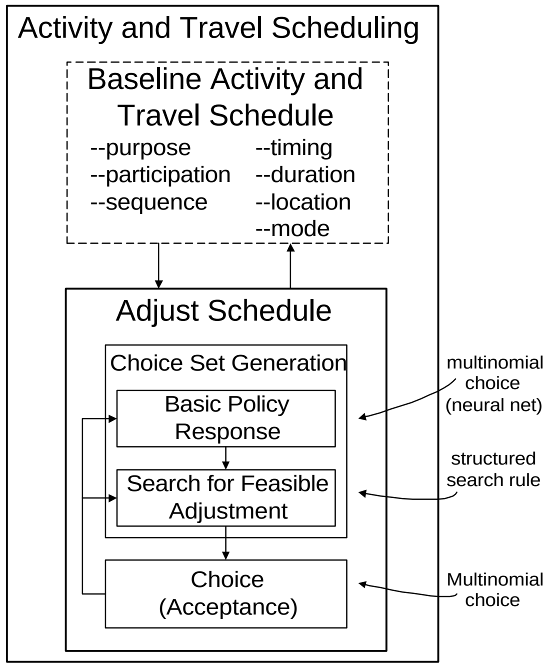


Figure 17: AMOS takes a detailed schedule and searches for an acceptable adjustment to a specific policy change. The process involves the selection of a basic policy response which narrows the domain of search. This is followed by the search for one feasible adjustment and the decision to accept the adjustment or continue the search.

The basic response model is policy specific. Six policies are included in the prototype for Washington, D.C.:

1. Workplace parking surcharge
2. Improved bicycle and pedestrian facilities
3. combination of 1 and 2
4. Workplace parking surcharge with employer-supplied commuter voucher
5. Peak period driver charge
6. combination of 4 and 5

The basic response is modeled as a multinomial choice from a set of eight alternatives:

1. No change
2. Change departure time to work
3. Switch to transit
4. Switch to car/vanpool
5. Switch to bicycle
6. Switch to walk
7. Work at home
8. Other

The prototype implements the multinomial choice model via the combination of a neural network and a multinomial logit model (MNL). The neural network predicts an output signal for each alternative, which is a scalar function of 36 decisionmaker characteristics under the policy change. The MNL converts the output signals to probabilities by using the output signal as the only explanatory variable in the utility function. The parameters of the basic response model are estimated from data supplied by a policy specific stated preference survey.

Given a basic response, a context specific search rule is used to find a feasible schedule adjustment. Figure 18 shows a portion of the prototype's search rule for a basic response of mode change from single occupant vehicle to transit. The rule checks first for the presence in the baseline schedule of stops on the way to work. If it finds some, it assumes they can't be chained in the new transit commute, and switches them into a home-based tour before work. Then it checks to see if the revised schedule allows for timely arrival at work. The rule continues like this to make schedule adjustments and feasibility checks, eventually arriving at a feasible alternative. Each time a schedule adjustment is needed, the adjustment is made via an intuitive decision rule or a simple choice model. The entire rule allows, in order of priority, changes to sequence and at-home stops, mode, and timing.

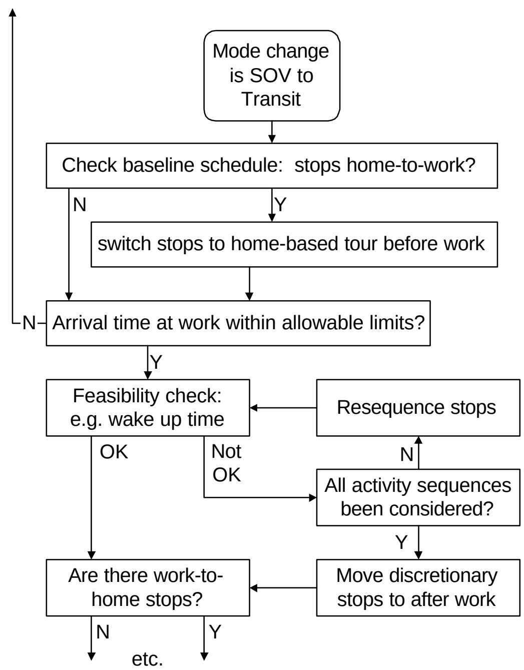


Figure 18: A portion of AMOS's context specific search for a feasible schedule adjustment, given the basic policy response of a mode change from single occupant vehicle to transit. (source: RDC Inc. 1995)

In summary, AMOS has two key features. First, it is a policy specific switching model. Because it is anchored in a baseline schedule and predicts switches based on policy specific survey data, it has great potential to be very informative in predicting short term responses to specific policy changes. The second key feature is the three step decision protocol of basic response, structured search and satisfaction-based decision.

AMOS has a few weaknesses linked to its design. First, it requires custom development for each policy. Second, validation is needed for each specific policy response model, and the availability of revealed preference data for this validation is very unlikely. Third, it doesn't forecast long run effects. Fourth, it requires the exogenous forecast of a baseline schedule for each application of the model. Fifth, the basic response and search models may inadequately represent the search process; the structured search sequence may not match the way some people search, and may systematically bias the predicted outcomes. Beyond these five design-related weaknesses, the prototype implementation of AMOS suffers from an incomplete scope; it is unable to predict changes in non-work schedules, or changes in activity participation, purpose, duration or location.

SMASH: sequential schedule building

SMASH (Figure 19) starts with a detailed activity program similar to that required by STARCHILD. Through an iterative process it gradually builds a schedule using activities from the program. In each iteration it starts with a schedule (a blank schedule in the first iteration) and conducts a generic non-exhaustive search, enumerating all schedule adjustments which would insert, delete or substitute one activity from the agenda. It then chooses one of the potential adjustments from the choice set and continues the search, or accepts the previous schedule and ends the search. Conceptually, the model could be used as a rescheduler, being rerun after the conduct of each activity, but the prototype was not implemented in this way.

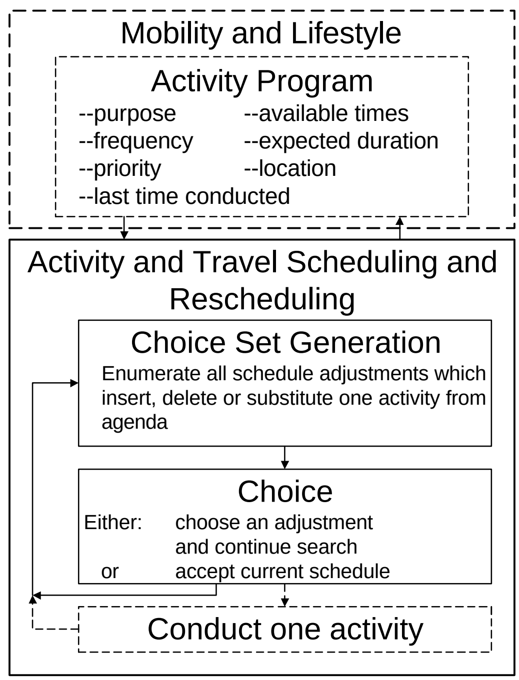


Figure 19: SMASH starts with a detailed activity program and an empty schedule. Then it builds the schedule by adding, deleting or substituting one program activity at a time. A decision is made each time whether or not to accept the current schedule and stop the building process.

The choice between schedule adjustment and schedule acceptance is implemented as a nested logit model. Schedule acceptance occurs when the utility of the schedule acceptance alternative is greater than that of all the schedule adjustments under consideration in the iteration. A schedule is more likely to be accepted if it has a lot of scheduled activity time, little travel time, includes the high priority activities from the program and lacks schedule conflicts.

The key feature of SMASH is the schedule construction process with a cost-benefit based stopping criterion. SMASH has three major weaknesses. First, it relies on an externally supplied detailed activity program which includes several important dimensions of the activity schedule, including desired participation, purpose, duration, location and mode of travel. Second, it requires a very complex survey for model estimation. Respondents must step through the entire schedule building process. Finally, the non-exhaustive search heuristic may be inadequate, and needs to be validated. Its method of restricting the search domain may systematically exclude alternatives which people frequently choose.

COMPARISONS OF THE EXAMPLES

We close this presentation with a summary comparison of the six example model systems which were examined in the two previous sections. In this comparison we look first at the major differences. Then we look at the three major categories in which the system requirements were presented, comparing the models' theoretical weaknesses, the scope of the systems and their susceptibility to practical problems.

Table 3 summarizes the major differences among the model systems in terms of the categories of differences we identified earlier. We see the two major classes of model systems. The econometric models are systems of equations predicting probabilities of outcomes, whereas the hybrid simulations are systems of sequential rules predicting decision process outcomes. The econometric models can be implemented as either probability or realization models, because they assign a probability to each modeled outcome, and the hybrid simulations are all implemented as realization models, simulating the choice of a single outcome for each individual in the representative population. The trip and tour-based econometric models are household models, while the daily schedule model and all the hybrid simulations sacrifice the household framework in implementing a representation of an entire day's schedule. AMOS is the only model system designed and implemented as a switching model.

	SubClass	Probability vs Realization	Household vs Individual	Switch vs Synthetic
Econometric Models				
MTC	Trip	P or S	H	Synthetic
Stockholm	Tour	P or S	H	Synthetic
Ben-Akiva & Bowman	Daily Schedule	P or S	I	Synthetic
Hybrid Simulations				
STARCHILD	Classify	S	I	Synthetic
AMOS	Satisficing Adjustment	S	I	Switch
SMASH	Schedule Building	S	I	Synthetic

Table 3: Major differences among the 6 example systems

Table 4 lists the major theoretical weaknesses of each of the 6 systems. The primary weakness of the trip-based MTC system and the tour-based Stockholm system is that they fail to integrate the trips or tours in a complete daily activity schedule. The daily schedule of the Ben-Akiva and Bowman model overcomes this weakness but is left with a utility-based decision protocol with an unrealistically large choice set. Each of the hybrid simulations can be challenged as to the validity of its decision protocol. In each case, specific assumptions about how the decisionmaker goes about the search and decision are structured into the simulation. These assumptions may be wrong in enough cases to invalidate the model's parameter estimates and predictions.

Econometric Models	
MTC	Does not explicitly model tours or integrated time of day
Stockholm	Does not link tours in a daily activity pattern, or integrate the time dimension
Ben-Akiva & Bowman	Large choice set is behaviorally unrealistic
Hybrid Simulations	
STARCHILD	Sample of alternatives may inadequately represent choice set
AMOS	Basic response and search may inadequately represent the search process
SMASH	Non-exhaustive search heuristic may not include alternatives persons would choose

Table 4: Theoretical weaknesses of the 6 example systems

Table 5 identifies the major and minor scope weaknesses of the model systems. The trip-based MTC system and tour-based Stockholm system do not integrate task sequence and timing into the daily schedule decision. The design of the Ben-Akiva and Bowman model clearly incorporates the sequence and timing dimensions, although the prototype implementation did not fully achieve this integration. More importantly, the representation of time is in very coarse discrete categories, limiting its representation in the time dimension. All three of the hybrid simulations are missing critical dimensions of the decision. Not only would these dimensions be difficult to predict externally to the model system, but they are also integral components of the scheduling decision, made interdependently with the modeled dimensions. Finally, the policy specific nature of AMOS, with its requirement of custom development for every policy, limits its ability to flexibly handle a complete range of policy issues.

	Econometric Models			Hybrid Simulations		
System Requirement	MTC	Stockholm	Ben-Akiva & Bowman	STAR CHILD	AMOS	SMASH
Schedule dimensions						
Activity participation				X	X	
Purpose				X	X	X
Sequence	X	X	x			
Timing	X	X	x			
Location				X	X	X
Mode of travel				X	x	X
Resolution			X			
Policy scope					X	

Table 5: Model system scope. An X indicate a major weakness and an x indicates a minor weakness

Our final comparison is of the model systems' susceptibility to practical problems, summarized in Table 6. The trip-based and tour-based models have overcome the major practical problems, as proven by their implementation in comprehensive operational travel forecasting systems. An operational implementation of the Ben-Akiva and Bowman model will face challenges associated with the large daily schedule choice set; the size of the software development effort and the computational requirements grow substantially with the choice set size. STARCHILD and AMOS, with structured, context specific search rules, make development and maintenance of software to represent the search process a particularly daunting task. AMOS's design as a policy-specific switching model make the provision of model validation data from before and after the policy implementation virtually impossible, and SMASH's requirement of schedule construction data for model estimation is also problematic.

	Econometric Models			Hybrid Simulations		
System Requirement	MTC	Stockholm	Ben-Akiva & Bowman	STAR CHILD	AMOS	SMASH
Data						
estimation						X
validation					X	
prediction					X	
Logic (software)			X	X	X	
Computation (hardware)			X			

Table 6: Practical problems of the model systems

SUMMARY

We started this presentation by asserting that the motivation for activity based travel forecasting is that aggregate phenomena of concern to governments are rooted in the activity based travel decisions of individuals.

We then examined the theory underlying activity based travel forecasting methods. The decision framework of activity and travel scheduling decisions includes urban development decisions of governments, developers and firms; the long range mobility and lifestyle decisions and within day implementation and rescheduling decisions of individuals; and the performance of the transportation system. Important characteristics of activity and travel demand include the notions that travel demand is derived from activity demand; household membership influences individual decisions; and capability, coupling and authority constraints, including our existence in a time-space continuum, limit our activity and travel choices. Choice theory identifies a variety of decision protocols, all of which fit in a two stage process of choice set generation and choice. Finally, individuals use coping mechanisms in order to make decisions with limited resources when the alternative set is as large and complex as that of the activity and travel scheduling decision.

We identified the basic characteristics of the various modeling approaches. We first noted the combinatorial nature of the modeling problem and listed the requirements of theoretical soundness, scope and practicality which the systems must satisfy. The commonalities among the modeling approaches include the decision framework, the two-stage choice process and the use of disaggregate methods. We classified the differences among the approaches along 4 dimensions. The major classification distinguishes econometric models from hybrid simulation models. Each model system can also be classified as representing either household decisions or individual decisions, by its operation as a synthetic model or a switching model, and by whether it predicts probabilities or simulates outcomes.

We described 6 important examples of attempts to incorporate activity based methods into travel forecasting models., including 3 econometric model systems and 3 hybrid simulations. The econometric model systems are systems of equations predicting probabilities of decision outcomes. They focus their attention on the choice stage of the decision protocol. These systems achieve the needed simplification of the combinatorial problem by aggregating alternatives and subdividing the decision outcomes. In order of simplicity, the three examples include a trip-based system, a tour-based system, and a system which represents an individual's entire daily schedule. The first two examples are theoretically inferior because they fail to integrate the sequence and timing of activity and travel decisions, and important associated constraints. However, they are the only two examples which have been implemented and validated operationally. The daily schedule system integrates the sequence and timing decisions in the daily schedule, but introduces complexity which has not yet been implemented and validated operationally.

Hybrid simulations are systems of sequential decision rules predicting decision process outcomes. Based on theories which emphasize human inability to rationally consider all the alternatives in complex decision situations, these systems focus attention on choice set generation. They achieve simplification by assuming a specific search method and subdividing the decision process into separate sequential steps. The first example assumes a classification method of choice set generation, the second assumes a particular structured search for a satisfying schedule adjustment, and the third assumes a sequential schedule building process. Additionally, all hybrid simulations developed to date achieve simplification by omitting important dimensions of the activity and travel scheduling decision. The hybrid simulations have very challenging data requirements for model estimation, application and validation, and the assumptions they make about the search process have not been validated.

POSTSCRIPT

We briefly consider three questions of interest which our presentation did not attempt to address.

Which activity based modeling approach is best? Our goal in this presentation was to establish a framework in which the different approaches can be understood and evaluated, and to begin that comparative evaluation. However, we intentionally stopped short of selecting a best approach. Indeed, this would be premature, because the most progressive approaches exist only as prototypes and have not been validated.

What are the future prospects of activity based travel forecasting? The need for better forecasts, their basis in activity theory, and the advance of computing technology all strongly favor the development and use of activity based travel forecasting systems. On the other hand, development costs and risks, and in some cases data requirements, are substantial. They present major roadblocks which will be difficult to overcome in an environment where planning is underfunded and compliance is more important than quality.

What about TRANSIMS? We haven't reviewed TRANSIMS (Barrett et al. 1995) because it doesn't yet address most of the activity and travel scheduling decisions. Figure 20 shows TRANSIMS in the context of the activity and travel decision framework we have used in this presentation. The vast majority of TRANSIMS effort so far has been in the Implementation and Rescheduling box, with the development of a detailed traffic microsimulation. A route planner, which encompasses the mode and route choices of the activity and travel scheduling box, supplies the simulation with its input. Except for the mode choice, which it handles, the route planner requires detailed schedule input nearly equivalent to the outputs of the activity based systems we have reviewed. The scheduling approach has not been specified in TRANSIMS.

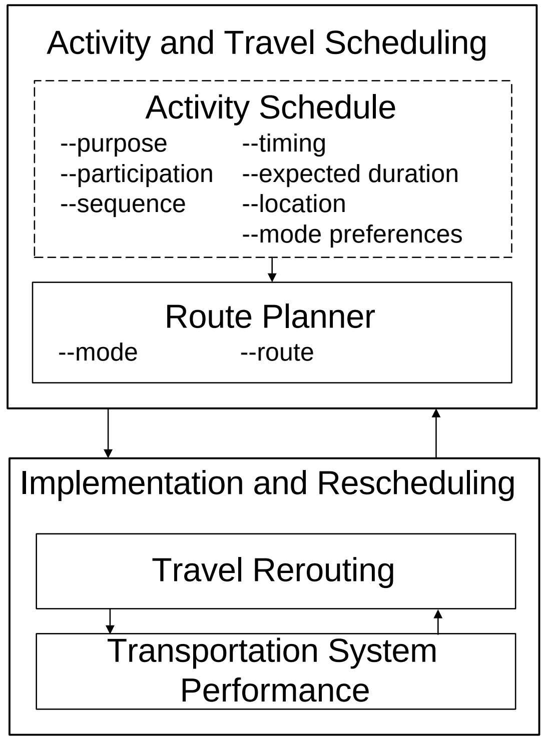


Figure 20: TRANSIMS development has focused on a traffic microsimulation which addresses travel rerouting decisions and the performance of the transportation system. A route planner takes activity schedule information from an as yet undefined activity scheduler, adds mode and route choice information, and supplies it to the microsimulation.

REFERENCES

Algers, S., A. Daly, P. Kjellman and S. Widlert (1995). Stockholm Model System (SIMS): Application. 7th World Conference of Transportation Research. Sydney, Australia.

Barrett, C., K. Berkbigler, et al. (1995). An Operational Description of TRANSIMS. Los Alamos, New Mexico, Los Alamos National Laboratory.

Ben-Akiva, M., J. Bowman and D. Gopinath (1996). "Travel Demand Model System For the Information Era." Transportation **publication pending**.

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

Ben-Akiva, M.E. and J.L. Bowman (1995). "Activity Based Disaggregate Travel Demand Model System with Daily Activity Schedules." Transportation Research B (pending).

Bowman, J.L. (1995). Activity Based Travel Demand Model System with Daily Activity Schedules, Massachusetts Institute of Technology.

Cascetta, E., A. Nuzzolo and V. Velardi (1993). A System of Mathematical Models for the Evaluation of Integrated Traffic Planning and Control Policies, Laboratorio Richerche Gestione e Controllo Traffico, Salerno, Italy.

Chapin, F.S. (1974). Human Activity Patterns in the City: Things People Do in Time and Space. New York, Wiley.

Daly, A.J., H.H.P. van Zwam and J. van der Valk (1983). Application of Disaggregate Models for a Regional Transport Study in the Netherlands. World Conference on Transport Research, Hamburg.

Ettema, D., A. Borgers and H. Timmermans (1993). "Simulation Model of Activity Scheduling Behavior." Transportation Research Record(1413): 1-11.

Ettema, D., A. Borgers and H. Timmermans (1995). SMASH (Simulation Model of Activity Scheduling Heuristics): Empirical Test and Simulation Issues. Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns. Eindhoven, The Netherlands.

Gunn, H.F., A.I.J.M. van der Hoorn and A.J. Daly (1987). Long Range Country-Wide Travel Demand Forecasts from Models of Individual Choice. Fifth International Conference on Travel Behaviour, Aiix-en Provence.

Hagerstrand, T. (1970). "What About People in Regional Science?" Regional Science Association Papers **24**: 7-21.

Hague Consulting Group (1992). The Netherlands National Model 1990: The National Model System for Traffic and Transport, Ministry of Transport and Public Works, The Netherlands.

RDC Inc. (1995). Activity-Based Modeling System for Travel Demand Forecasting. Washington, D.C., US Department of Transportation and US Environmental Protection Agency.

Recker, W.W., M.G. McNally and G.S. Root (1986a). "A Model of Complex Travel Behavior: Part II--An Operational Model." Transportation Research A **20A**(4): 319-330.

Recker, W.W., M.G. McNally and G.S. Root (1986b). "A Model of Complex Travel Behavior: Part I--Theoretical Development." Transportation Research A **20A**(4): 307-318.

Rich, E. and K. Knight (1991). Artificial Intelligence. New York, McGraw-Hill.

Ruiter, E.R. and M.E. Ben-Akiva (1978). "Disaggregate Travel Demand Models for the San Francisco Bay Area." Transportation Research Record **673**: 121-128.

Simon, H. (1957). Models of Man. New York, Wiley.

Tversky, A. (1972). "Elimination by Aspects: A Theory of Choice." Psychological Review **79**: 281-299.