Activity-Based Travel Forecasting Conference

February, 1997

TMIP

Travel Model Improvement Program

Department of Transportation
Federal Highway Administration
Federal Transit Administration
Office of the Secretary

Environmental Protection Agency

Department of Energy

U.S.Department of Transportation

U.S.Environmental Protection Agency

Travel Model Improvement Program

The Department of Transportation, in cooperation with the Environmental Protection Agency, has embarked on a research program to respond to the requirements of the Clean Air Act Amendments of 1990 and the Intermodal Surface Transportation Efficiency Act of 1991. This program addresses the linkage of transportation to air quality, energy, economic growth, land use and the overall quality of life. The program addresses both analytic tools and the integration of these tools into the planning process to better support decision makers. The program has the following objectives:

1. To increase the ability of existing travel forecasting procedures to respond to emerging issues including: environmental concerns, growth managements, and lifestyles along with traditional transportation issues,

2. To redesign the travel forecasting process to reflect changes in behavior, to respond to greater information needs placed on the forecasting process and to take advantage of changes in data collection technology, and

3. To integrate the forecasting techniques into the decision making process, providing better understanding of the effects of transportation improvements and allowing decisionmakers in state governments, local governments, transit agencies, metropolitan planning organizations and environmental agencies the capability of making improved transportation decisions.

This research was funded through the Travel Model Improvement Program.

Further information about the Travel Model Improvement Program may be obtained by writing to:

TMIP Information Request
Metropolitan Planning (HEP-20)
Federal Highway Administration
U.S. Department of Transportation
400 Seventh Street, SW

Activity-Based Travel Forecasting Conference, June 2-5, 1996

Summary, Recommendations, and Compendium of Papers

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INTRODUCTION

The principal goal of this conference was to promote use of activity-based approaches for travel forecasting. Corollary purposes were to identify activity-based forecasting techniques that can be used now and to recommend actions to advance the state-of-the-art. The conference was organized as one plenary session and three workshops.

This report includes papers that document the keynote address and five other presentations in the plenary session. Konstadinos Goulias' keynote address laid out the issues regarding activity based travel forecasting that were to be addressed at the conference. Martin Lee-Gosselin then presented a synthesis of experience with activity based forecasting. Richard Beckman described the approaches to activity based analysis used in the TRANSIMS model. Eric Pas summarized recent research and advances in activity based analyses. Keith Lawton described applications of activity and time-use data for transportation planning in Portland, Oregon. Ryuichi Kitamura described other applications of activity information for forecasting travel behavior. Eric Miller reported on applications of microsimulation for activity based forecasting. A paper based on the introductory seminar presented at the conference is also included here.

Following those papers are summaries of the discussions and recommendations in the three workshops:

- Data Resources and Survey Methods for Activity Analysis
  - ✦ Chaired by Martin Lee-Gosselin and John Polak
  - ✦ With discussions by Kay Axhausen, Ken Cervenka and Christopher Fleet
- Models of Activity and Travel Behavior
  - ✦ Chaired by Eric Pas and Ram Pendyala
  - ✦ With discussions by Charles Purvis and Thomas Golob
- Microsimulation in Activity Analysis
  - ✦ Chaired by Robert Sicko and Hani Mahmassani
  - ✦ With discussions by Konstadinos Goulias and Richard Beckman

The workshops began by considering techniques that are currently available for activity based travel forecasting. Gaps in the availability and workability of those techniques were identified, and research and development were recommended to overcome those deficiencies.

The first workshop examined the kinds of data needed for activity forecasting and the resources and procedures for obtaining that data. The content and structure of activity and time-use diaries were discussed. There have been at least six major regional activity diary surveys in the United States: Portland, Dallas, Honolulu, Boston, Washington, DC, and Triangle Transit Authority (North Carolina). The progression of those surveys represents significant developments in activity diary survey techniques. Much can be learned in the near term by examining the data from those surveys and from the successes and failures of the travel behavior analyses and forecasts using that data. Needs identified include improving panel methods, event based data collection, stated response methods and including transportation service supply data.

The second workshop considered models of activity engagement and their relationship to travel behavior models. Three discrete choice models have been implemented: a Dutch national model, a Stockholm model and work by Cambridge Systematics, Inc., in Boise, Idaho. The latter has also been applied in a statewide model for New Hampshire. Some additional work in Portland is in progress. The discussions dealt with data requirements for those models and how to interface with currently conventional models. The strengths and weaknesses of various approaches were identified and remedial actions were recommended.

The third workshop examined the potential for microsimulation in activity analysis and forecasting. This technique holds opportunity for forecasting person and household characteristics and possibly inputs to travel forecasting models as well. The discussion also addressed the special needs of microsimulation procedures. Those techniques are currently being developed for use in the new TRANSIMS models. Two microsimulation approaches that have been applied are the AMOS work in Washington, DC, and the Midas model for microsimulation of demographic change in the Netherlands. Also, an extension of AMOS, adding in-vehicle transactions is being applied in California but was not yet complete at the time of the conference.

Most comments indicated that the conference was useful because it brought together researchers and practitioners to introduce and discuss the need and potential for new procedures. The practitioners were exposed to some new developments that may improve their practice in the future. However there was disappointment that the state-of-the-art had not yet reached the point of providing tested techniques that the practitioners could use now. The researchers were apprised of the needs of practitioners as guidance for their development efforts.

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

[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.

INTRODUCTION

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

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

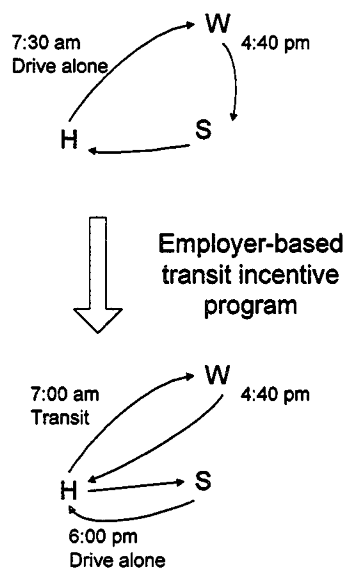
We'll first look at the motivation for activity based forecasting. Then we'll examine the concepts underlying the methods. We'll identify the basic characteristics of the various modeling approaches, considering the requirements the systems must satisfy, the characteristics they have in common and the 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.

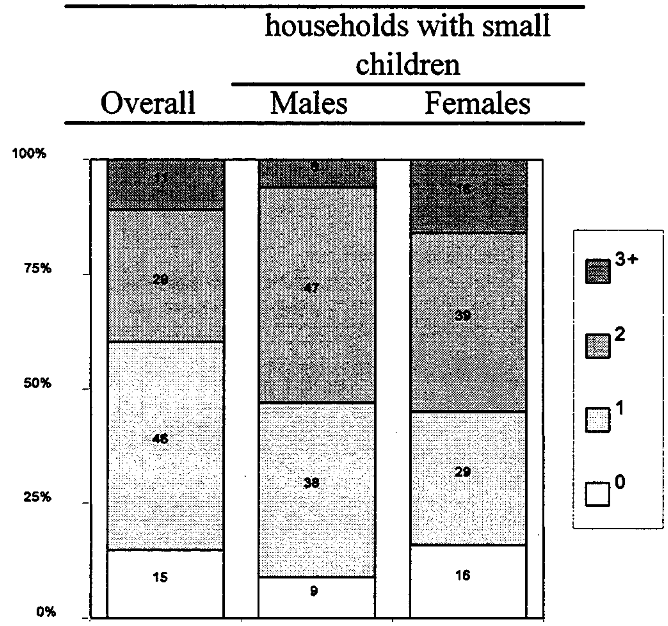
Concerns about aggregate phenomena such as congestion, emissions and land use patterns lead governments to consider policies aimed at controlling them. These include, for example, employer-based commute programs, single occupant vehicle regulation, road pricing, multimodal facilities and transit oriented 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)



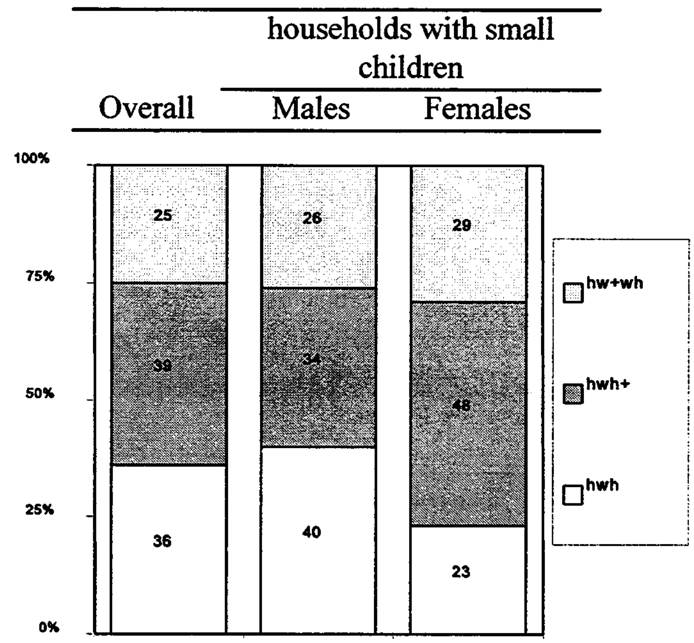
In Table 1 we see that mode choice differs between primary and secondary tours in the day. Drive alone and transit alternatives drop in market share for secondary tours, with substantial increases in shared ride and walk alternatives.

Table 1
Modes of travel on primary and secondary tours

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

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.

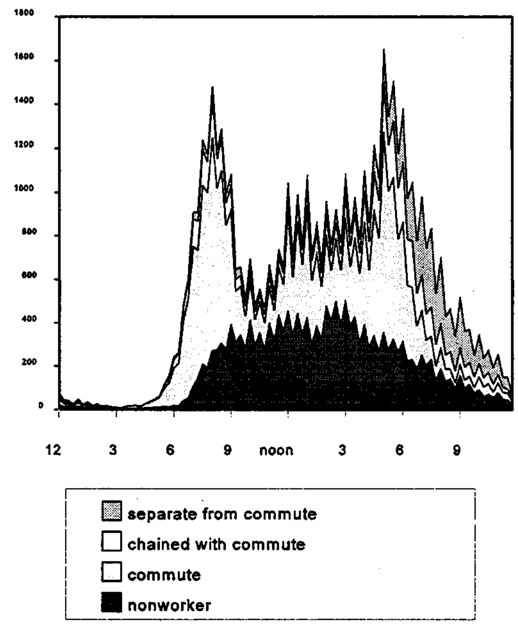
Figure 3
Complexity of the work commute tour



+ = one or more additional stops

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.

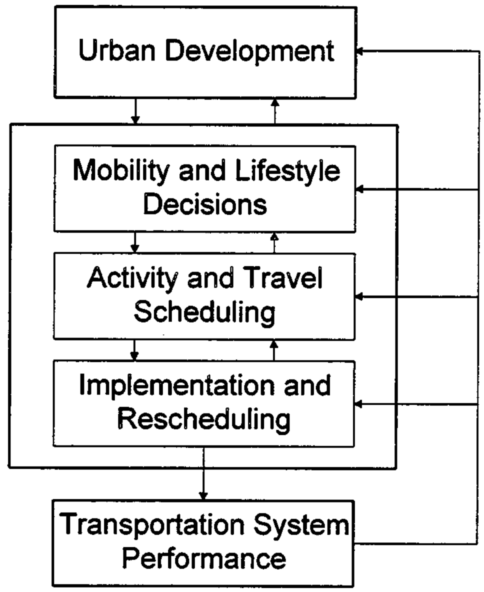
THE THEORY BEHIND ACTIVITY BASED TRAVEL FORECASTING

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 time frames of decisionmaking. Mobility and lifestyle decisions occur at irregular and infrequent intervals, in a time frame 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.

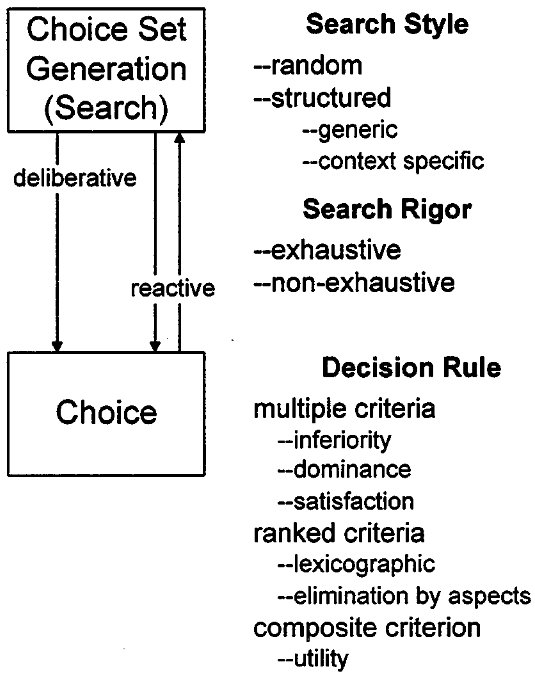
Every choice has three important elements, including (1) a set of alternatives, (2) a decisionmaker, and (3) a decision protocol, or set of rules. The set of all feasible alternatives is often referred to as the universal set, whereas the set of alternatives which the decisionmaker actually considers 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.

Table 2
An estimate of the number of daily activity
schedule alternatives facing an 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}**

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.

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

- 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

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.

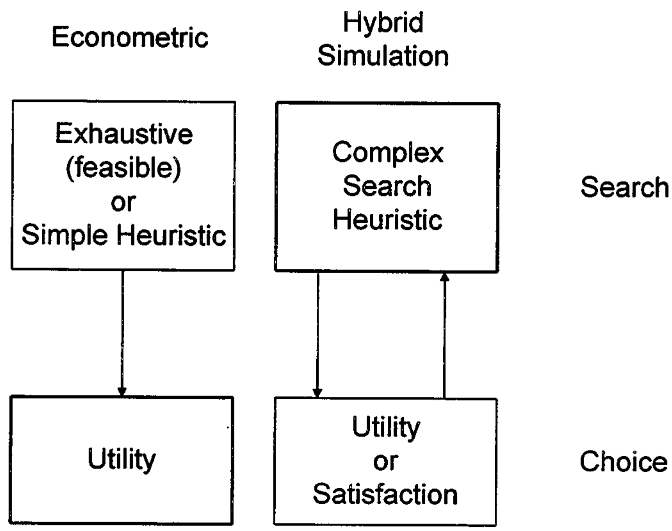
Differences Among the Various Modeling Approaches

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.

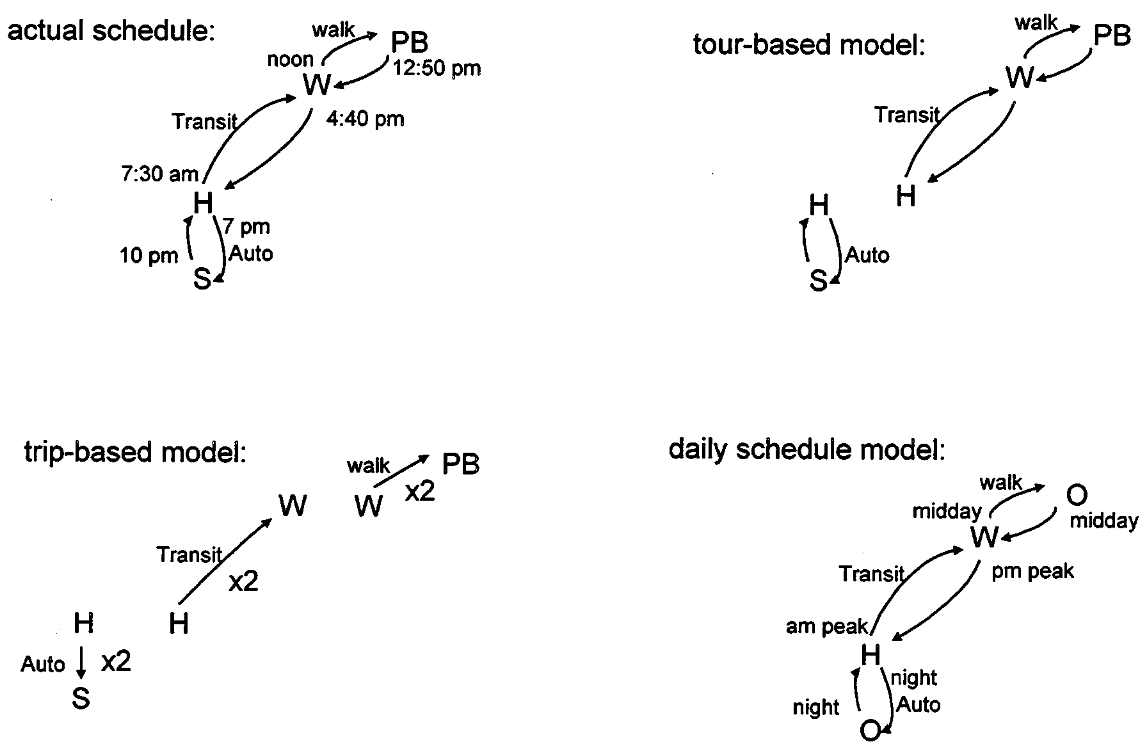
As we explained already, econometric model systems are systems of equations representing probabilities of decision outcomes. They are based on the theory of probability and statistics, generate probabilities for all alternative outcomes, and are usually based on a utility maximization assumption. Typically,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

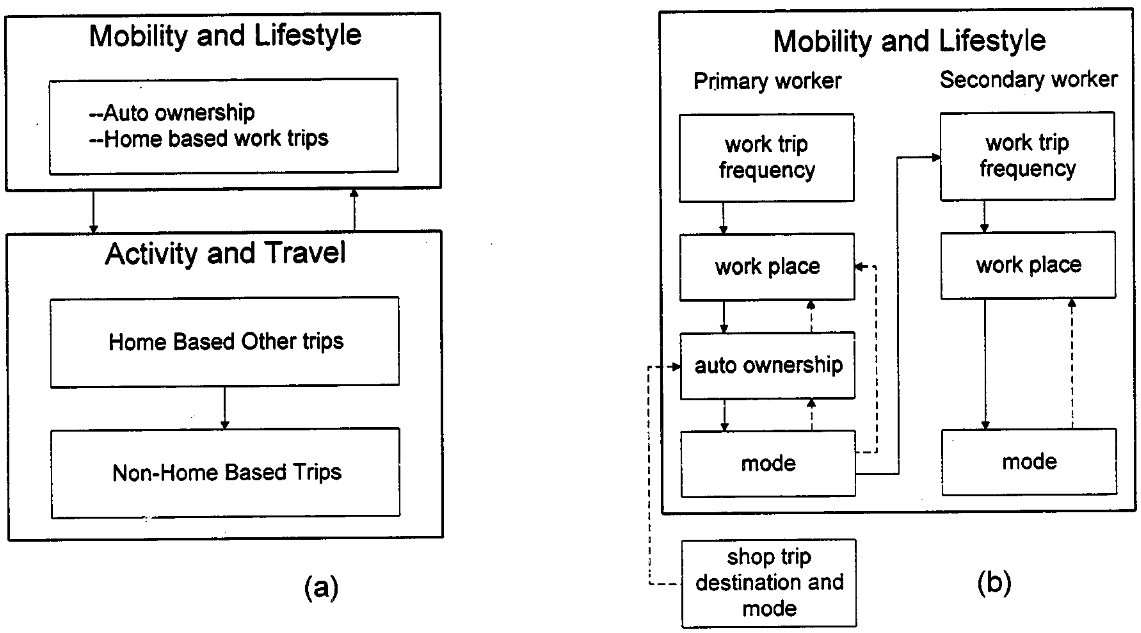
Figure 9
The three subclasses of econometric model systems are characterized by how they subdivide the daily schedule outcome. Trip-based models subdivide the schedule into one-way trips. Tour-based models separate the schedule into tours. Daily schedule models explicitly link the tours.



Trip-Based System

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)

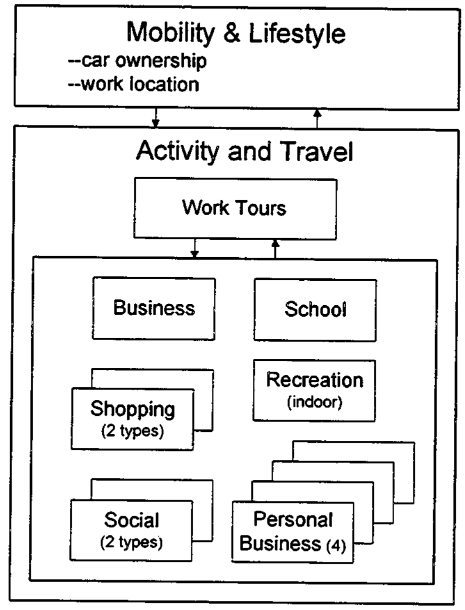


In summary, key features of the trip-based model systems, exemplified by the MTC system, are their composition of disaggregate choice models and their integration via conditionality and measures of expected utility according to the decision framework. Their key weakness is the sequential modeling of 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.

Tour-Based System

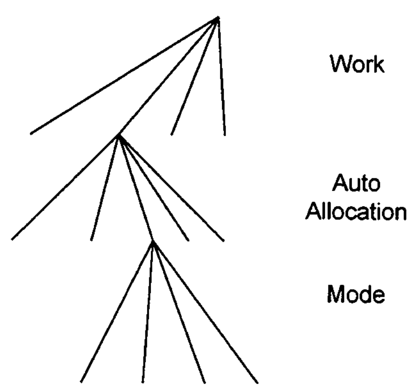
Tour-based systems were first developed in the late 1970's and 80's in the Netherlands (Gunn, van der Hoorn and Daly 1987; Daly, van Zwam and van der Valk 1983; Hague Consulting Group 1992), and are being used extensively there and elsewhere in Europe, with the most recent systems being developed in 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



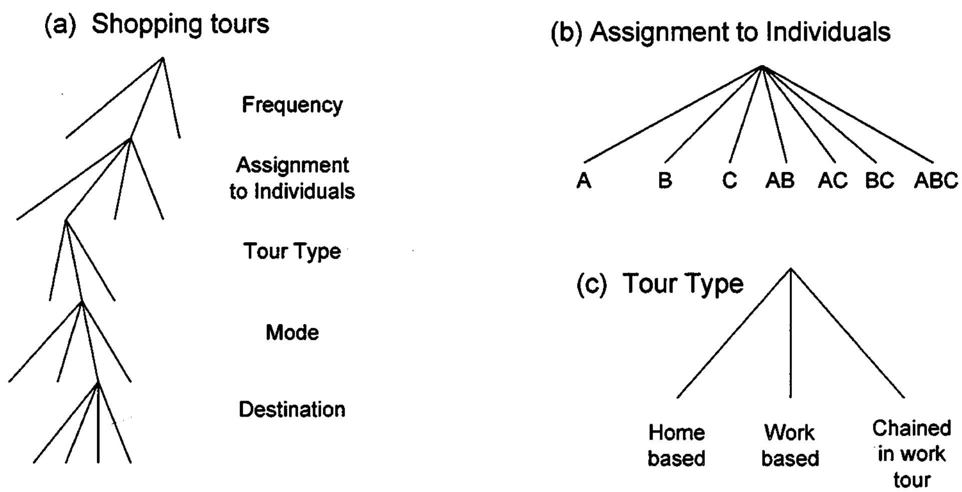
The work tour decision, Figure 12, is modeled as a nested logit model. It includes the household's decision of who will work today, how the household's autos will be allocated among the workers, and the mode of travel for workers who do not use a household auto.

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 en route 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).



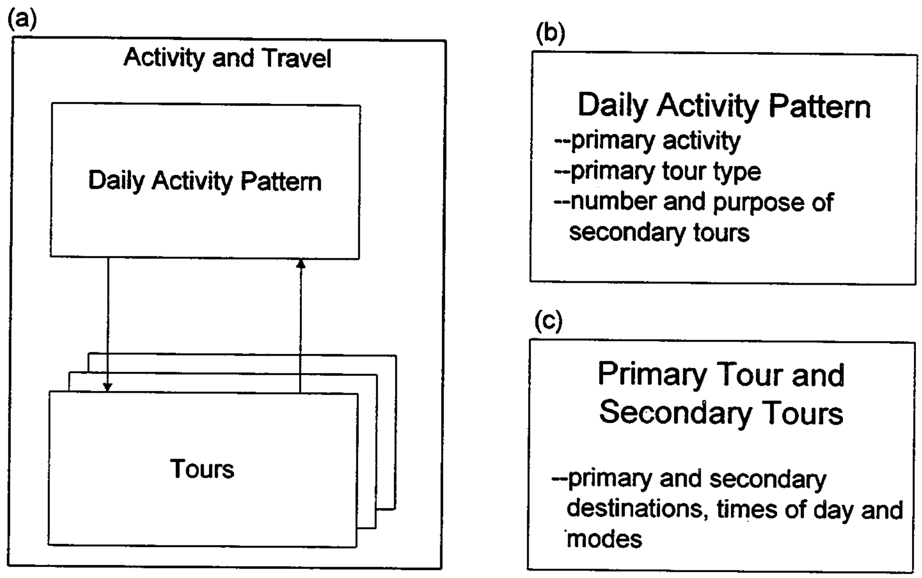
Summarizing the tour-based econometric approach, the key feature is the explicit representation of tours, and trip chaining within tours. The Stockholm example also explicitly models household decisions. The key weaknesses of the tour-based systems are that they lack an overarching pattern connecting 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

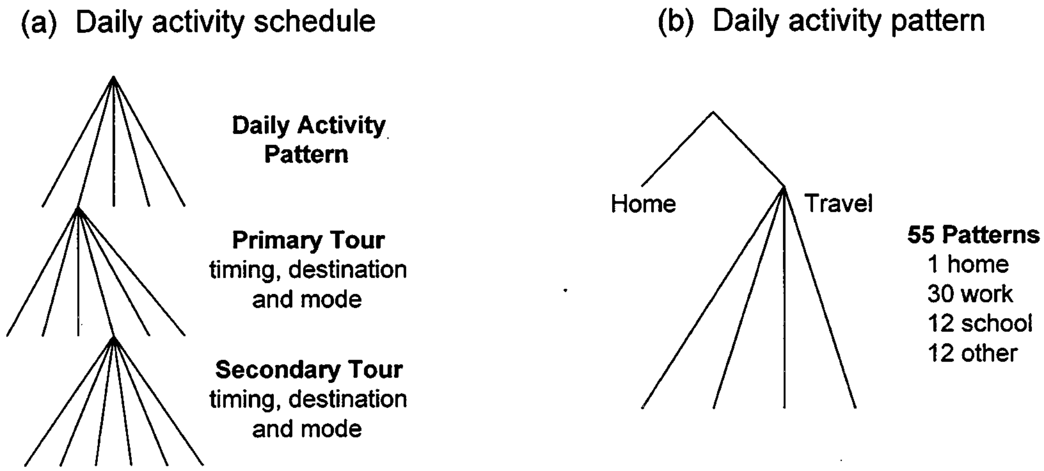
The daily schedule system (Ben-Akiva *et. al.* 1996; Ben-Akiva and Bowman 1995; Bowman 1995) deals directly with the two weaknesses of the tour-based models. First, it explicitly represents the choice of a daily activity pattern, which overarches and ties together tour decisions (Figure 14). Second, 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

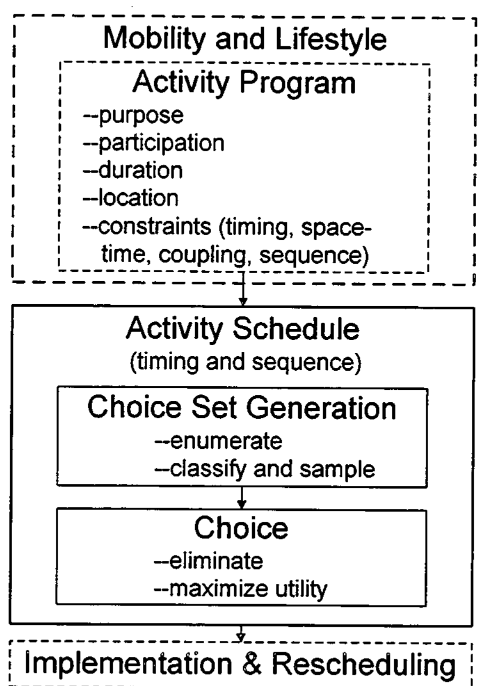
We have already described hybrid simulations as sequential decision rules predicting decision process outcomes, and noted their focus of attention on choice set generation. These systems are based on various decision theories, such as cognitive limitation or the notion of a search which terminates with 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.

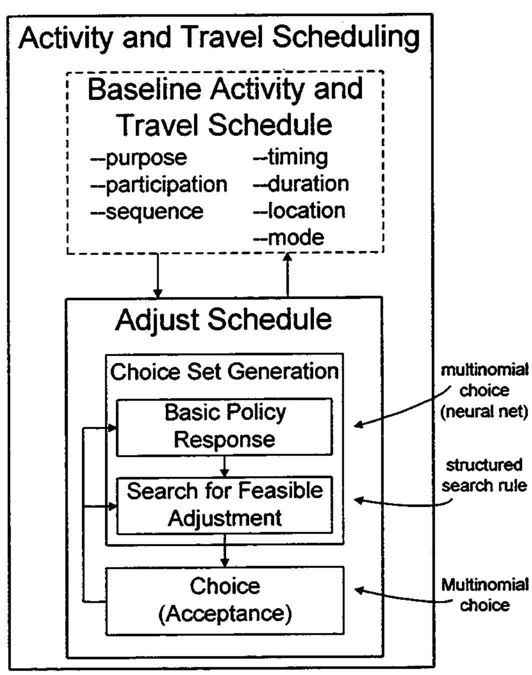


STARCHILD's key features are its detailed representation of constraints in the identification of feasible alternatives, and the use of a classification method to generate the choice set. As a model intended for use in forecasting travel, it has two key weaknesses. First, it relies on external sources 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, DC:

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

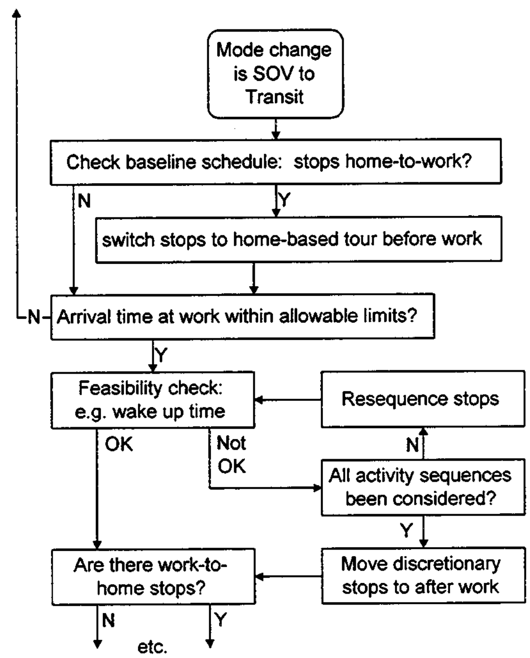
The basic response is modeled as a multinomial choice from a set of eight alternatives:

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.

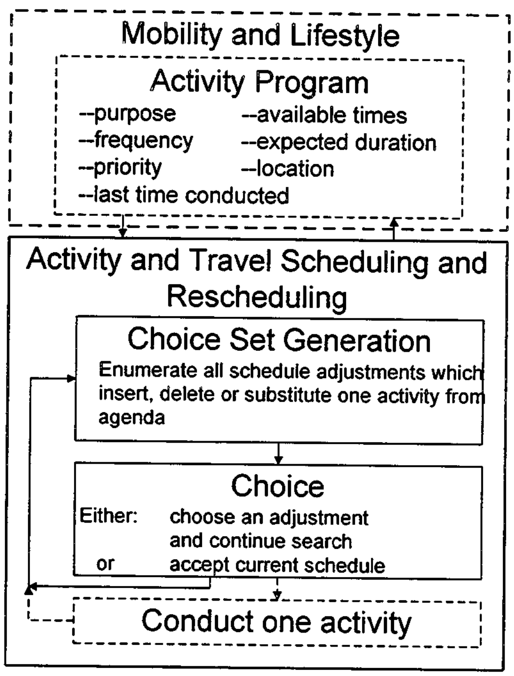
AMOS has a few weaknesses linked to its design. First, it requires custom development for each policy. Second, validation is needed for each specific policy response model, and the availability of revealed preference data for this validation is very unlikely. Third, it doesn't forecast long run effects. 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.

Table 3
Major differences among the 6 example systems

	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 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.

Table 4
Theoretical weaknesses of the 6 example systems

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 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.

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

	Econometric Models			Hybrid Simulations		
System Requirement	MTC	Stockholm	Ben-Akiva & Bowman	STARCHILD	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	

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.

Table 6
Practical problems of the model systems

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

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

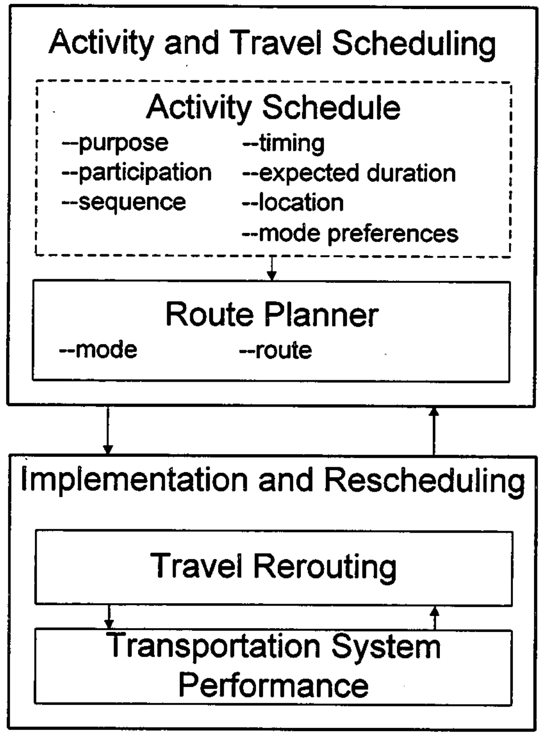
We briefly consider three questions of interest which our presentation did not attempt to address.

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.



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ACTIVITY-BASED TRAVEL FORECASTING: WHAT ARE SOME ISSUES?

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INTRODUCTION

Models for activity-based travel forecasting methods are increasingly developed by researchers mainly in Europe and the United States in support of policy actions that cannot be addressed by existing modeling methods and forecasting applications (see Hofman *et. al.*, 1995, and Mierzejewski, 1996). Since the 1980s, when activity methods were considered as predominantly esoteric research approaches with very few applications (Kitamura, 1988, Jones, 1990), significant progress has been done in the three areas of data collection, modeling, and simulation that are the subject of this conference. In this paper a brief review of some issues that need to be addressed in the short and long terms are presented. Past unresolved forecasting issues and the policy context in the U.S. with an example from a program announced recently by the U.S. DOT are first provided. The paper continues with the basic definitions underlying activity-based forecasting methods and models and a brief description of accumulated evidence-knowledge that is found in the literature today. Specific issues for which some exploratory research is needed are also outlined. These issues are further developed and artificially categorized into short-term (in need of immediate answers and provision of evidence) and long-term issues that are presented as a straw man strategic plan for a successful activity-based travel forecasting system that could become the standard practice in the U.S. Specific issues to be targeted by the workshops in this conference are provided last.

NEEDS AND POLICY CONTEXT

Dissatisfaction with trip-based forecasting tools and attempts to move practice toward activity-based approaches predates the milestone legislation of the 1990s in the U.S. (Allaman *et. al.*, 1982). Indeed, issues such as forecasting the inputs to travel demand equations emerged as early as the first development and application of disaggregate choice models (Tye *et. al.*, 1982), which need detailed sociodemographic information at the level of a trip, an individual, and/or a household. Similarly, when aggregate approaches are used (e.g., at the traffic analysis zone), forecasts of sociodemographic information of the residents need to also be provided and many methods used in practice are gross approximations that produce many errors throughout the forecasting exercise (Hamburg *et. al.*, 1983). The 1980s research on this subject was partially in response to legislation such as the Federal-aid Urban System and the requirement for Metropolitan Planning Organizations to produce long range transportation plans, transportation systems management plans, and a list of transportation projects (the transportation improvement program-TIP). Public agency support (by Urban Mass Transit Administration, UMTA, today called Federal Transit Administration, FTA) for the Urban Transportation Planning System (UTPS) made the four-step procedure - trip generation, trip distribution, (trip-based) modal split, traffic assignment- the standard forecasting tool for evaluating large scale urban facility building in the 10- to 20-year horizons. The development of this tool took more than 30 years to mature (for example compare the 1950s applications in Detroit, Chicago, and Pittsburgh to the later UTPS-like systems in Seattle, Portland, and San Francisco among many others). Over time, however, the need for more accurate forecasting tools that contain richer analytical and forecasting instruments to address policy actions has been identified and documented (Bajpai, 1991, provides an example) and has yet to be satisfied. Indeed, emphasis was given more to the development of operational traffic engineering tools to study short term improvements (e.g., the TRAF-NETSIM, FHWA, 1994).

In the past five years, the need to examine new and more complex policy initiatives is becoming increasingly pressing since the passage of the Intermodal Surface Transportation Efficiency Act of 1991. The intermodal character of the new legislation, its congestion management systems that are mandatory for metropolitan areas with more than 200,000 people, and the taxing air quality requirements for selected U.S. regions motivate many forecasting applications. Substantial forecasting improvements can be clearly seen in a series of applications that have also been motivated by the Clean Air Act Amendments of 1990 (CAAA) that dictates impact assessment of transportation control measures and the creation of statewide mobile source air pollution inventories (Stopher, 1994, Loudon and Dagang, 1994, Goulias *et. al.*, 1993). Lack of funding for transportation improvement projects also motivates the need for impact fees' assessment for individual private developments, which in turn necessitates higher resolution for the regional council forecasting models and interfacing with traffic engineering tools that are recognized in state and local impact fee legislation (for examples see Levinson and Koepke, 1992, and other papers in the same volume).

This urgency for new forecasting tools is further compounded by the technology "push" under the general name of Intelligent Transportation Systems (i.e., bundles of technological solutions in the form of user services that attempt to solve chronic problems such as congestion, safety, and air pollution). Under these initiatives, forecasting models, in addition to long term land use trends and air quality impacts, need to also address issues related to technology use and information provision to travelers. Indicative of this are recent policy initiatives, such as "Operation Timesaver," which increase the modeling and forecasting demands for large metropolitan areas because of the shorter time frame for creating these policy analysis tools. Operation Timesaver was announced by U.S. DOT at the 1996 Transportation Research Board Annual meeting. The objective of this program is to achieve travel-time reduction(s) of at least

15 percent using Intelligent Transportation Infrastructure (ITI) deployed in 75 of the largest U.S. metropolitan areas within the next 10 years through an investment of $150 billion dollars. The intended infrastructure will contain smart traffic-control systems, freeway management systems, transit management systems, incident management programs, electronic toll collection on roads and bridges, electronic fare payment, railroad grade crossings that are integrated into the overall system, emergency response providers, and travelers' information systems. The U.S. DOT's vision is that with advanced technology investment we can create much more of the capacity we would have provided by building new highways (e.g., $10 billion investment in ITI is expected to provide two-thirds of the capacity needed). This public relations activity shows clearly what is expected of local regional planning agencies in terms of modeling and analysis. One of the goals of this initiative is to create transportation systems with measurable deliverable goals through a demonstration effort in which the future system is developed in stages and at each stage quantitative estimates of expected benefits need to be provided. This is something that the UTPS-like procedures were not designed for and obviously are unable to address. In a hypothetical "timesaver" metro plan we should expect metropolitan areas to provide access and better level of service using enabling technology (from the ITS portfolio of technologies). Since this operation is motivated by ISTEA and it is geared toward what is expected to emerge from the ISTEA reauthorization it is more likely that transportation demand and supply management will have a multi modal character and will be based on information provision and use by travelers and traffic managers.

Ultimately, ITI time saving initiatives enable people's freedom in time allocation (e.g., if 15% of their travel time is saved, they may use it for leisure and recreation activities or maybe additional work). Current travel demand analysis and forecasting practices are not sensitive to these shifts in time allocation because the temporal dimension in the UTPS-like procedures is totally absent (e.g., to compute the peak hour traffic flow gross factoring is performed on daily traffic forecasts) and under the best case scenarios partially present through some sort of post-processing.

Ongoing policy initiatives place more complex issues in the domain of policy analysis and forecasting to regional councils. In addition to the need for air quality modeling and transportation demand management impact assessment, regional councils need to also evaluate the impacts of new technologies, information provision, and pricing/financing strategies (e.g., tolls). To do this, their forecasting capabilities need to be more accurate and detailed in space by increasing the level of resolution of the current traffic analysis zones to capture much smaller geographic units. Consider for example the interesting exercise of estimating the regional effects of a corridor information management system and strategies that involve signal timing at intersections. They also need to predict traffic by time of day at time-slices that are much finer than the typical "AM-peak," "PM peak," and the "remainder of a day" types of daily segmentations. In addition to this increased resolution and fidelity of forecasting, other temporal scales need to be considered instead of the single time point forecast in the distant future. This emerges clearly from the need to consider the effects of staging in project development, which needs to be incorporated into the usual long range planning process and the submission of TIP projects with related impacts and comparisons in terms of costs, benefits, and cost effectiveness.

This is particularly important for projects that attempt to influence travel demand and transportation supply at the same time.

Most important, however, there is a more basic need for data, models, and forecasting methods that have been developed from real-life experiences with some of these "new" policy actions. Projects for which impact assessments are needed are ongoing and will be emerging in the next two to five years from policy initiatives such as operation timesaver. It is clear, then, that for activity-based approaches one such initiative is an opportunity to demonstrate the superiority of activity-based data collection, modeling, and forecasting. While activity-based methods have the highest potential to address issues of this type, there is no hard evidence from field tests (e.g., validated and verified models that have worked in the regional council context). If activity-based approaches are to become successful in practice, we, as a transportation community, need to begin implementing and testing these models immediately using current projects as operational tests (very much like the use of technologies' operational tests in the Intelligent Transportation Systems arena).

ACTIVITY-BASED FORECASTING

An activity-based travel forecasting system is a system that uses as inputs sociodemographic information of potential travelers and land use information to create schedules followed by people in their everyday life providing as output, for a given day, detailed lists of activities pursued, times spent in each activity, and travel information from activity to activity (including travel time, mode used, and so forth). This output is very much like a "day-timer" for each person in a given region. A complete operational activity-based forecasting system does not exist yet. However, given the advanced state of research on the subject, we can envision a hypothetical activity-based forecasting system with the following as its basic ingredients.

Data on time use-allocation (Demand for Service): Information collected from persons on their current use of their time to participate in out-of-home and at-home activities and for travel from one activity location to another (called time allocation).

Data on activity opportunities and locations (Supply of Service): Information collected from places where people can actually pursue activities, including home. It also includes other attributes of activity participation such as availability, access, cost, etc.

Person and household time use (activity and travel) profiles: These are the models of time allocation that function the same way as the typical UTPS-like models for travel albeit in a much more complex form and providing more detailed information for analysts and planners.

An evolutionary engine (from t to t+x): Clearly the "snapshot" approach, a single time point in the distant future, to forecasting is surpassed. Alternate future scenarios are much more useful to decision makers because of the general trends they show rather than for their exact values of the forecast parameters. Some sort of mechanism that makes a region to evolve over time through the different stages of sociodemographic, and demand-supply changes is needed to depict the paths of, for example, traffic changes and reveals the instances at which policy intervention is needed. One such engine is called micro simulation.

Interface with other forecasts: The charge of forecasting regional needs is not limited to transportation. Economic development, housing, water supply, sewage systems, and recreation facilities are some other important areas that interface with transportation and they are within the planning domain of regional councils. Forecasts are also provided for these areas using a variety of methods (e.g., sociodemographic forecasting by cohort-based methods, housing needs by micro-economic methods, and economic development by macro-economic models). All these methods need to be interfaced together to at least provide consistent forecasts.

An activity-based forecasting system needs data for model estimation/calibration and simply as basic inputs. Following the typical subdivision of data and models into demand for service and supply of service, following are specific examples of data needs.

Demand Side:

1. Longitudinal and geographic information on time use/allocation (activities, travel, opportunity locations, activity participation durations, and so forth)
2. Sociodemographics (age, gender, employment status, occupation, and so forth).
3. Knowledge of opportunities and level of service offered to people by the activity locations and the system that brings either people to the activities (transportation) or the activities to people (telecommunication).
4. Use of technology and information (e.g., use of personal computers)
5. Household resource availability (e.g., car ownership, housing characteristics, telecommunication equipment ownership, etc.)

Supply Side:

1. Spatial and non-spatial inventory of activity opportunities (e.g., shopping and teleshopping availability by time of day)
2. Daily, day-of-the-week, and seasonal opportunity windows (e.g., periods during which specific activities can be pursued)
3. Networks of spatial and non-spatial activity opportunities (e.g., transportation and telecommunications networks)

Assuming, then, that data on demand and supply are available (see the "Data" workshop summary in this conference), the next ingredients are models that will transform the data inputs into specific policy action impacts through observed and postulated relationships. These basic components are listed below with a brief description:

Sociodemographics and time use profiles: These are functions that are able to depict how different people use their time differently.

Household members' activity allocators: Task allocation within a household is one of the major determinants of behavior. These are the functions that show which activities are associated with which member of a given household. These allocators could be also extended to other social groups to reflect tasks and associated activities when people are members of organized or spontaneous groups (e.g., a firm and its employees, a neighborhood and its residents).

Activity & travel equations: These are the equations and routines that map specific activity pattern behaviors to specific travel behavior (for examples see Hamed and Mannering, 1990, Kwan, 1995, Recker, 1995, Ben-Akiva and Bowman, 1995, Ettema *et. al.*, 1995, Pendyala *et. al.*, 1995, Ma and Goulias, 1996, Golob, 1996, Golob and McNally, 1996, and Golob *et. al.*, 1996).

Spatio-temporal models of supply: This is a set of functions that perform the same mapping of time-use to sociodemographics in the demand side and are needed in supply to correlate geography with activity opportunity and ultimately predict the desirability of locations.

Residence-workplace relocation and time use: In the U.S. changing jobs and/or residence is a frequent phenomenon. In this process people go through stages of "cognitive disengagement" from the previous workplace and/or residence and phases of "cognitive engagement" with the new workplace and/or residence. As a result their activity and travel patterns go through changes that should be captured by the activity-based travel forecasting system.

Telecommunications-information and time use: Telecommunications are used today either intentionally or unintentionally to affect the ways people spend their time. For example, telecommuting has been proposed as a method to mitigate traffic congestion. In this forecasting system, models that represent the use of telecommunications and information by people to participate in activities and travel should also be included.

Lifecycle-lifestyle changes and time use: Lifecycle and associated lifestyle are important determinants of time use allocation by individuals and their households. The changes in lifecycle and concomitant changes in time use allocation need to also be reflected in the forecasting system in a similar way as it is done in travel demand.

Seasonal and day-of-the-week time use profiles: Time use may change dramatically within a week (e.g., a weekday versus weekend) but also based on seasons (e.g., consider the shopping and related activities people pursue during the period of Thanksgiving to Christmas in the U.S.). Models need to incorporate these fluctuations if forecasting is to be done for these periods of time that are usually excluded from the traditional UTPS-like procedures.

Long-term trends in time use: In addition to the usual source of information for transportation models (e.g., models from data collected on a representative day or data spanning a few years), we also need models that depict longer term trends. For example, to estimate models representing the changing roles and resulting time allocation between men and women and respective roles in society.

EVOLUTIONARY ENGINE

Given the data and models outlined above, a forecasting system needs also a routine that uses the data as inputs and in which the models are embedded to produce forecasts. In practice, these are a series of logical statements that given an input population in a region create evolutionary paths of change from a given time point to the next using computer software. We can call this a micro simulator because it operates at the level of a single microscopic unit (e.g., a person, a household, or a vehicle). It is a simulation because we numerically exercise a set of models for a given set of inputs to produce forecasts (as opposed to the use of a closed form and mathematically exact solution to predict the future). Lack of knowledge and the inherent randomness of human behavior dictates the need to design these systems with at least randomness in input components making the evolutionary engine a stochastic micro simulator (Law and Kelton, 1991, and for a more complete and focused exposition see Miller, 1996, in this volume).

An evolutionary engine attempts to replicate the relationship among sociodemographics, land use, time use, and travel. The causal links among these groups of entities can be extremely complex and in many instances unknown or incompletely specified. This is the reason that no closed form solution can be created for such a forecasting model system. In terms of capabilities, however, the engine needs to provide a realistic representation of person and household life evolution (e.g., birth, death, marriages, divorces, birth of children, etc.) and spatio-temporal activity opportunity evolution while at the same time it accounts for uncertainties in data, models, and behavioral variation.

INTERFACE WITH OTHER FORECASTING WORK

Many regional councils (MPOs) have made substantial investments not only on UTPS-based forecasting systems (e.g., software) and data to "feed" their models (e.g., travel diaries and detailed trip-by-trip mode-specific information) but also on training and education of technical staff and elected officials. On one hand, as expected there is some resistance to accept and adopt new forecasting tools that obviously threatens to replace not only the UTPS-like models but also UTPS "experts." On the other hand, however, there may be a place for these old-fashioned forecasting techniques (e.g., as a backup to the new methods). Independently of whether activity-based forecasting methods are designed as substitutes or complementary to the existing methods, before their consideration we need to identify specific gains that MPOs may realize by moving toward activity-based methods today (e.g., begin to think of transportation service provision as a service that should eliminate barriers from peoples' productive life). Indeed, from a time-use perspective new user-benefit measures emerge (Gershuny, 1994, Kitamura *et. al.*, 1996). These measures are much more realistic and understandable than the nebulous concept of level of service (e.g., volume over capacity on a link of a network). In addition to a planning focus shift that may require time, the use of existing data needs to be looked at carefully. For example, in the recent past, regional councils have engaged in data collection using travel diaries in surveys (one-day, two-day, etc.). The data from these surveys may be a good source of information for activity-based approaches that can be used to answer some of the policy questions MPOs face. In addition, no regional council has attempted to collect time-use data over time spans that are longer than two-days. Data from repeated travel diaries have been collected and, from the behavioral standpoint and resulting model formulation, substantial gains will emerge from their analysis (e.g., the Puget Sound Transportation Panel at the Puget Sound Regional Council). Similarly, time use databases exist in the U.S. and they cover many years providing a rich source of information for changes in behavior over time. Maybe, then, one way to transition into activity-based forecasting would be to formulate models using data from these secondary sources, to be incorporated into the UTPS-based forecasting systems.

One of the motivations for this conference is that, on one hand, research-since the 1980s when activity-based methods were simply research experiments-has provided us with some undeniable evidence of its potential, while on the other hand, we are still unable to assess the capabilities of activity-based approaches as forecasting methods that are able to replace the aging UTPS-like procedures. We know, for example, that activity-based forecasting is more realistic because it deals with the way people allocate their time, it provides temporally rich information (i.e., detailed schedules of activities at high resolution-minute by minute, hour by hour) that can be used by traffic simulation software, it is based on a more natural framework that is easier to explain to decision makers, and it supports the development of better cost and benefits service measures leading to better planning. From the developmental viewpoint, research has produced new estimating frameworks (see Axhausen and Garling, 1992) and the approach is theoretically rich allowing to examine more complex issues (e.g., Golledge, 1995). There are, however, many unknowns about activity-based forecasting. For example, there is no evidence about the accuracy/precision (or predictive capabilities) of activity-based models, the activity opportunity-supply data requirements have not been examined and assessed for feasibility, their interface with existing methods is absent, little information is available regarding model building and maintenance costs, their apparent complexity to non academic audiences is threatening, and tests of possible model transferability are totally absent.

If activity-based travel forecasting is to be used in the short-term, we need success stories with proof of concept applications (i.e., a showcase). Given the prolific research activity in this field, however, the need arises for an organized impartial, and independent inventory and assessment of activity data collection methods and activity-travel methods and models. When applicable this inventory should include an examination of an interface with UTPS (e.g., building on STEP development in Harvey and Deakin, 1996) and a study of early demonstrations such as in the Portland, OR, metropolitan area. The creation of an activity-based travel forecasting method should be preceded by field experiments with, for example, one or more purely activity-based forecasting systems compared to hybrid methods that use existing resources and improvements to the four-stage approach. In addition, micro simulation is well established in traffic analysis and seems to begin to be accepted as a source of sociodemographic forecasting data. These field tests can include micro simulation in the form of TRANSIMS but also other simpler and less hardware-software demanding methods for smaller problems. Since alternate approaches to solve the same or similar problems may lead to specialized applications (e.g., methods for large MPOs in non-attainment areas versus methods for small MPOs with seemingly no air quality problems), parallel streams of development seem a reasonable route. This is particularly important because it sets the stage for the long-term R&D program. Most important, however, given the experience accumulated in ITS with operational tests, an independent evaluation of these field tests should be done. This will provide important input for the long-term development of activity-based methods. Strong evidence that can provide a proof to healthy skeptics about the forecasting capabilities of an activity-based approach should be a **"showcase."** This could be the assembly of a variety of techniques and models that have the potential of providing undeniable evidence of superiority over existing methods. For example, the showcase should contain routines and models that predict sociodemographics using micro simulation, which is a proven technology. While micro simulation is needed for the "dissagregate" information necessary for activity-based models it also provides the information needed for the more aggregate UTPS-like models such as income and employment. It could also contain routines/models that represent the activity supply inventory for forecasting (e.g., using Geographic Information Systems to pinpoint opportunity locations). Again, this may have a dual use for activity-based models and for better UTPS-like methods that attempt to identify specific generators of traffic for equitable traffic impact fee determinations (see Chung and Goulias, 1996). Then, the usefulness of time use profiles can be demonstrated in terms of their evolution over time, e.g., supply changes as a result of normal fluctuation (morning versus evening) an/or as a result of policy actions (e.g., land use ordinances and zoning regulations). Critical to this demonstration is the validation of forecasting using repeated surveys of the same people and geographic locations. The last ingredient of a showcase and not the least is engagement of a regional council as an active participant in this process. Indeed, the Portland regional agency, which may be a good candidate for showcase, is an active player in activity-based forecasting and it is realizing some of the benefits of activity-based approaches.

One of the accomplishments of this conference (and of the TMIP program) may be a vision of one or more future activity-based travel forecasting methodologies. This longer term R&D program should consider: (1) Data collection and modeling programs; (2) policy analyses to support; (3) benefits, risks, and costs; and (4) outreach and training. More specifically, however, from the methodological viewpoint, attention needs to be paid on the role longitudinal activity surveys may play in developing new methods (e.g., there is no repeated over time - panel - survey that collects time-use data in the U.S. for transportation research). In addition, methods to compare models in terms of their predictive performance are inexistent or very rudimentary while this topic is an open debate in other fields. A subject related to this regards research needed to develop these methods together with model verification and validation. None of the existing forecasting methods, travel and activity-based, is able to address systematically and comprehensibly current policy problems. Indeed, there is no method that can compare transportation system management strategies to transportation demand management strategies in terms of air quality benefits. Also, future policy problems (e.g., impact of widespread use of cellular communication for trip planning purposes) need to be identified and targeted by new development research efforts. From a TMIP operations viewpoint coordination with land use research may lead to benefits to the activity-based forecasting development and land use research.

SUMMARY

Activity-based approaches are a necessity that emerged from recent legislation, unsatisfied technical needs accumulating for the past two decades, and technology applications in the U.S. and Europe. Current proposed approaches attempt to address new policy questions and chronic problems and frustration with the aging UTPS-based forecasting methods and the "times are right" for activity-based forecasting systems for many reasons. Knowledge about activity-based data collection is at a mature stage (see Richardson *et. al.*, 1995, Stopher, 1996, and Stecher *et. al.*, 1996), activity model estimation/calibration and related frameworks exist and have been implemented in various contexts, and long-term frameworks to be used for activity-based travel forecasting have been designed (e.g., Morrison and Loose, 1995, and Spear, 1994). In addition, evolutionary engines to perform long-term detailed forecasting based on stochastic micro simulation are available (Miller, in these conference proceedings). However, practical issues through demonstration/illustration of the methods remain unresolved largely due to lack of specific field-tests, which can be attributed to lack of focused funding. As a result early applications of activity-based methods are promising but incomplete and the need arises for one or more demonstrations that in turn can show evidence of the new method's superiority over conventional methods. One way to speed up the process, of introducing activity-based methods to regional councils' ongoing work, would be to integrate these new methods with existing forecasting work. In addition, many technology tests are under way throughout the U.S. and they offer a unique opportunity to develop and test activity-based methods. In light of this, then, this conference may need to address the following in the three parallel streams of workshops.

Data Issues: (1) Data Collection for forecasting (collection methods, secondary use of other data, inventories of databases) and (2) Data content and cost comparison with travel surveys and possible secondary use of other databases.

Model Issues:(1) Existence and availability of time use models (activity and travel) and (2) Model complexity, realism, clarity, and comparison in forecasting potential

(Micro)Simulation Issues: (1) Simulation and uncertainty treatment, (2) Sociodemographics-locational analysis - schedules and time use profiles, and (3) Evolutionary aspects.

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SYNTHESIS OF PAST ACTIVITY ANALYSIS APPLICATIONS

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ABSTRACT

This review describes the emergence of the central ideas within the activity analysis paradigm and their application to travel forecasting. We posit that three interconnected processes of "ideas applications" form the basis of scientific development. The first is conceptualization and theory building. The second is empirical tests and applications: here, we make a distinction between those in which activity patterns are considered as segmentation variables in travel models, and those in which travel is incorporated into activity patterns. The third process is the self-conscious evaluation of the interplay between theory and application: we call this last the "reflexive nexus." We provide examples of studies which demonstrate these processes; most studies emphasize one over the others. This framework places the pathways toward implementing activity-based travel demand forecasting into more of a cyclical, and less of a linear, historical context. One example is given of how all three processes have contributed to a particular of model of activity scheduling. We conclude that activity analysis continues to develop within waxing and waning periods of inductive theory construction and deductive theory testing. Extending activity analysis to the realm of travel forecasting should provide intellectually more satisfying forecasting tools and lead to improved theory.

1. INTRODUCTION

We intend this review to provide a map of activity analysis as applied to travel decisions of households. We make no claim to providing a complete and detailed map of the terrain; neither do we wish to leave the reader wandering in the wilderness. Rather, we intend to point out some of the major landmarks of activity analysis, to give the reader an overview of what activity analysis has accomplished and a perspective on how these accomplishments came about, and to prepare and motivate the reader to explore the terrain of activity analysis and its applications. We offer the following definition of, and motivation for, activity analysis before moving on to fill in our map.

1.1 WHAT IS ACTIVITY ANALYSIS?

Several reviews of the activity analysis literature have been written (e.g., Damm, 1983; Jones, 1983; Kitamura, 1988; Jones *et. al.* 1990; Axhausen and Gärling, 1992; Jones, 1995). Describing activity analysis, Damm (1983) states:

> "These [activity] decisions are not necessarily identical to or made simultaneously with travel decisions…Instead of focusing on what people do between activities, [activity analysis] researchers look at what people do between trips. In this vein, it seems more appropriate to refer to activity scheduling…especially if we assume that activities are more important than trips."

Jones *et. al.* 1990 provide this definition of activity analysis:

> "[it is a] framework in which travel is analyzed as daily or multi-day patterns of behaviour, related to and derived from differences in life styles and activity participation among the population."

These definitions contain two essential, and from the perspective of travel demand forecasting, revolutionary, ideas: the primacy of activities over travel and the primacy of people over vehicles. These ideas both allow, and require, that we begin to incorporate the wide variety of personal and social influences that shape both our expressed activity and travel choices, and more importantly, our freedom to act.

The practitioner of activity analysis generally takes the household to be the source of activity participation. Individual households and their members are the behavioral units that are the source of activity participation. Household members' choices of activities are mediated by systems of constraints that include the structure of family relationships within the household and by the resources available to the household. "Travel" occurs when people move from one activity to another separated in space and time.

Activity analysis defines a set of problems for study. This set includes, but is not limited to, studying how households create activity schedules, mapping activities in time and space, examining the linkages between people created by the roles they play within their households and other social groups to which they belong, tracing the resource allocations and constraints that limit activity choice, and as an outcome of these, examining the physical movements of people by specific modes and routes. Transportation researchers, planners and designers are concerned with these last outcomes, that is, with the choices of travel mode and timing, trip duration, and distance of the trips that link activities. With such information, existing transportation infrastructure can be managed, and new transportation systems and technologies evaluated.

1.2 WHY ACTIVITY ANALYSIS?

Any number of other recent articles and reviews reiterate the common arguments for shifting from a pre-occupation with where vehicles go, to analysis of what people do. The reasons may be summarized as being of two general types. First, there are criticisms of the inability of vehicle- and trip-based analyses to provide accurate models of travel and travel behavior. Second, vehicle and trip based models are not fully amenable to changing policy contexts that require managing transportation infrastructure and resources. Within the older "four step" transportation research and planning paradigm, the connections between land uses (which are aggregates of the types of activities that may be completed within a given geographic space) and travel were *ad hoc* models of trip attraction, trip generation, and travel impedance. The aspiration of activity analysis has always been to replace these *ad hoc* empirical specifications with testable theories of human behavior.

1.3 HOW DO WE DO ACTIVITY ANALYSIS?

As a transportation research paradigm, activity analysis is concerned with how households connect activities separated in space and time. To study how these connections are made, the activity analyst requires the understanding of several things: why households and their members engage in different activities, including the linkages between people that are the result of (or perhaps create) their household and social roles; the physical and social environments that provide opportunities for activities, resources to access these activities, and the constraints that limit access; how households and their members learn those environments; and how people process their activity needs and their knowledge of their environments to develop schedules of activities. These requirements have spawned searches for theories of activity participation, development of new data collection techniques (e.g., activity diaries and interactive interview and survey methods), and novel applications of mathematical techniques and models (e.g., pattern recognition algorithms, simultaneous equation systems, synthetic generation of households and vehicle fleets, and production systems).

1.4 CHARTING OUR COURSE

We take the distinction between activities and travel, and the primacy placed upon activities, as the point of departure between activity analysis and traditional "four-step" transportation planning and forecasting. In Section 2, we describe several key "emerging features" of activity analysis (Jones *et. al.*, 1990). No one of these features identifies an application as an "activity analysis," yet together they constitute the essence of this approach in which "activities are more important than trips." This section provides a little more definition of activity analysis for those readers to whom it may be unfamiliar, before exploring how we have arrived at where we are today.

Then, in Section 3, we trace the manner in which the underlying ideas of activity analysis have been applied. We present the history of the development of scientific knowledge in general, and activity analysis in particular, as intertwined paths of inductive processes of theory building and deductive processes of theory testing and empirical application. We identify three areas of "idea application": development of activity analysis as a framework for conducting forecasting, empirical tests and applications, and the reflexive interplay between theory construction and empirical testing and application.

The social theorist Anthony Giddens writes:

> "'Reflexivity' hence should be understood not merely as 'self consciousness' but as the monitored character of the ongoing flow of social life. To be a human being is to be a purposive agent, who both has reasons for his or her activities and is able, if asked, to elaborate discursively upon those reasons..." (1984).

Further,

> "Thus it is useful to speak of reflexivity as grounded in the continuous monitoring of action which human beings display and expect others to display." (ibid.)

Our ability to monitor and elaborate on, our awareness of, the interplay between theory and application causes us to pursue specific lines of inquiry, e.g., classification of problem domains. This paper itself is one example of a reflexive inquiry.

We will illustrate each process with a few examples only; our intention, as described above, is to highlight important landmarks; other authors in these proceedings are charged with presenting more detailed descriptions of some of the areas of empirical application we briefly describe. This process oriented history puts activity-based approaches into a more cyclical, less linear, historical context. We believe this context addresses concerns with describing developments in activity analysis in a linear sequences of distinct epochs, as raised by Gerardin (1990) in his response to Pas' (1990) review. Before concluding the paper, we show how all three processes have contributed to development one type of one particular model of activity scheduling.

2. FEATURES OF ACTIVITY ANALYSIS

The content of activity analysis is distinguished from other transportation research paradigms by several features. Jones *et. al.* (1990) identify seven "emerging features" of activity analysis:

1) Treat travel as a demand derived from desires and demands to participate in other, non-travel, activities;
2) Focus on sequences or patterns of behavior, not discrete trips;
3) Analyze households as the decision-making units;
4) Examine detailed timing and duration of activities and travel;
5) Incorporate spatial, temporal, and inter-personal constraints;
6) Recognize interdependence among events separated in space and time; and

7) Use household and person classification schemes based on differences in activity needs, commitments and constraints.

Based on the recognized importance of dynamic analysis, the need to examine activities over multiple time periods, and as an extension of Jones' *et. al.* sixth feature, we would add to this list:

8) Analyze activities and travel within longitudinal (dynamic) frameworks.

We illustrate these eight features with studies that include them. This list of examples is of course not a census of activity analysis. Also, we do not attempt to provide complete descriptions of each of the example studies, most of which include several of the features listed above.

1. Travel is derived from demand for participation in non-travel activities. This is simply a statement that very little travel is undertaken for its own sake: most travel is undertaken to engage in an activity at some other location (and future time). This feature has been operationalized in a number of ways. First, a number of theories of activity participation have been proposed, some examples of which are cited later in the paper (Section 3.2). Supernak (1990) develops a conceptual model of "activity utility". One (assumed) attribute of "utility" within his framework is that the utility of separate activities and the disutility of the separate trips to access them are cumulative (though he does not specify over what time period utility accumulates). He points out that by subordinating travel to activities and examining the combined utility of an entire daily activity schedule and the associated disutility of traveling to complete that schedule, one can offer explanations for...

> "...some disappointing results from disaggregate models applied to choices such as mode choice. A modelling effort aimed at minimizing disutility of travel may *easily misrepresent* the actual effort made by traveler i (or, rather, activity participant i) who is trying to maximize the overall utility of the action A (set of actions) that involves both activity and travel." (ibid.) (Emphasis in the original.)

One example of an attempt to operationalize a connection between activities and travel is contained in van Wissen *et. al.* (1991). They estimate a simultaneous dynamic travel and activity time allocation model. While recognizing that spatial dispersion and differences in the quality of activity locations, as well as differences in activity scheduling by individuals, are central to predicting travel based on activity patterns, they adopt a simplified framework in which travel time for each activity is proportional to the amount of time allocated to that activity.

2. Sequences or patterns of activities and travel. Tracing sequences or patterns of activities goes back at least as far as Hägerstrand's (1970) work on time-space paths. Recker *et. al.* (1983) applied pattern recognition algorithms to the problem of identifying patterns in household travel. Huff and Hanson (1986) characterize the degrees of repetition and variation in household travel activity patterns. Pas and Koppelman (1987) identify determining factors in the degree of variation in day-to-day travel of different people. They conclude that people with fewer economic and role related constraints, and those whose personal and household needs do not require daily participation in out-of-home activities, show the highest day-to-day variation in their travel.

Somewhat paradoxically perhaps, many analyses of activity and trip sequences have given particular prominence to the effect of one trip type (activity) on travel. The prototypical example is the work trip, going back to Cullen's (1972) identification of the work trip as a "peg" around which other activities are scheduled. Work trip studies form part of the basis for the three part distinction (home-based work, home-based non-work, and non-home based) employed by many researchers and practitioners today. Other examples of specific trip types that have received attention include Kitamura's (1983) analysis of "serve passenger" trips, Kim's *et. al.* (1994) examination of trip chains that contain shopping trips, and Sands and Smock's (1994) consideration of trips to places of worship.

Trip chaining is one example of how sequences of trips have been analyzed. Analyses of trip chains is an intermediate step between studying single trips and studying activity patterns; while giving attention to the inter-connection of some activities, focusing on single chains may fail to capture the connections between chains. The use of trip chain concepts continues to be emphasized in a number of studies and a session of the 1996 Annual Meeting of the Transportation Research Board appears to have been at least partially devoted to the practical application of trip chaining; three papers from that session deal with this subject (Vovsha, 1996; Schultz and Allen, 1996; Shiftan and Ruiter, 1996). In a departure from trip chaining, Axhausen (1990) proposes a method for combining models of activity chains with models of traffic network flows. Though further from practical application than trip chaining concepts, the recent efforts to develop models of activity scheduling (such as those cited below in Section 3.2) offer the most complete treatment of how households plan to execute sequences of activities.

The idea of patterns of behavior has been contrasted with variance, variability and other measures of non-patterned behavior. The existence of patterns of activity participation is implicit in the seventh item in this list of features of activity analysis. Classification requires that we be able to group households that are more like each other than they are like members of other groups.

3. Analyze households as the decision-making units. We make the following distinction between this feature and the seventh in this list: we illustrate this point with studies of decision-making within households; we will illustrate the seventh point with studies that employ household and person classification schemes as variables to segment the analysis of activity schedules or travel. Examples of recent analyses of decision-making within households include Ahrentzen's *et. al.* (1989) analysis of gender roles in the allocation of space, time and activities within the home, Kiker and Ng's (1990) test of a simultaneous equation model of spousal time allocation under conditions of interindividual and interactivity simultaneity, Solberg and Wong's (1991) test a Gronau model of household allocation of time to leisure, home production, market work and work related travel and Manke's *et. al.* (1994) study of the distribution of in-home labor between women, men and children.[2]

4. Examine timing and duration of activities and travel. There has been a distinct cycle of methodological developments in the treatment of activity duration. Early efforts analyzed activity duration within the framework of discrete choice models and utility maximizing behavioral models, e.g., Kitamura (1984). Later, van Wissen *et. al.* (1991) applied a system of simultaneous equations to a dynamic analysis of household allocation of time to out-of-home activities and travel. In the latest revisitation to modeling activity duration, hazard models are being applied, e.g., Hensher and Mannering (1994), Ettema, Borgers and Timmermans (1995), and Niemeier and Morita (1995).

5. Incorporate spatial, temporal and inter-personal constraints. Analyses that address one or more of the types of constraints range from time and space constraints explored by Kitamura *et. al.* (1990), to the household roles explored by Niemeier and Morita (1995). A particular focus of this research has been the evolution of gender roles and the reconciliation of personal and professional demands (Hanson and Hanson, 1980; Greico *et. al.*, 1989).

6. Recognize interdependence among events separated in space and time. As one example, a recent study explores the interdependence of separate events within the activity patterns of a single person (Purvis, Iglesias and Eisen, 1996). This study show an inverse relation exists between work trip duration and the frequency of home based, non-work trips: as the duration of the work trip increases, the likelihood of making non-work trips from home, after arriving home from work, goes down.

7. Use household and person classification schemes based on differences in activity needs, commitments and constraints. This statement clearly implies that household and person classification schemes should be based on differences derived from activity participation. It has been far more common though that household and person classification schemes have been based on the characteristics of people. Clarke and Dix (1983) point out that household level classifications are widely used in trip generation models.

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[2] The Ahrentzen *et. al.* (1989) and Manke *et. al.* (1994) studies are concerned with the allocation of space, time, and activities solely within the home and might therefore seem to be out of place in a paper on activity-based applications to travel forecasting. We include them because in-home activities have been widely, and incorrectly, ignored in travel analysis. One study of the effect of work trip duration on non-work trip generation was unable to distinguish whether workers, who were at home, were there because they were ill, on vacation, telecommuting, or on a scheduled day off, because no questions were asked about in-home activities (Purvis *et. al.*, 1996). Further, despite the importance of home as a center of a wide variety of activities, all in-home activities are often grouped together as if they were a single activity. However, the reasons we travel to home at a specific time and at a particular point in a sequence of activities may be linked to a specific activity to be done at home.

Household classifications based on "lifecycles" or "life stages" use socio-economic variables as proxies for differences in activity needs, commitments and constraints. These life stages are defined primarily by the presence or absence of children, age of children, age of heads of household, number of heads of household, and employment or retirement status of household members. Clarke and Dix (ibid.) analyze the relationship between lifecycle groups and time budgets. Their results indicate the existence of systematic variations in how adults in some household types spend their time. There are, however, types of households whose adults' time budgets cannot be clearly distinguished. They reason:

> "That we could not distinguish between [some] groups...on this [lifecycle] basis does not necessarily mean that households in these groups are homogeneous. They comprise families with no children under five and older couples with no children, and although they exhibit similar activity budgets...they may well experience different constraints on their behaviour which result from the structure of their families." (ibid.) [Ellipses added.]

This result echoes the caution sounded by Brög and Erl (1980) that descriptors of people may not capture the relevant attributes of their subjective evaluations of their objective "situations." Their concern is echoed by empirical work by Kunert (1994), who concludes that "even for well defined person categories, interpersonal variety in mobility behavior is large but has to be seen in relation to even greater intrapersonal variability."

However, analysis of activity participation and travel by socio-economic and demographic groupings can be instructive and may be appropriate for questions of equity. As an example, Hanson (1977) analyzes transportation deprivation of the elderly by comparing their travel to that of the non-elderly population.

Also based on socio-economic classifications, Ferguson (1990), for example, examined how household composition affected choices of residence location and the journey to work; Strathman *et. al.* (1994) compared differences in trip chaining and non-work travel between households grouped by demographic structure.

8. Analyze activities and travel within longitudinal (dynamic) frameworks. There are several reasons for making explicit the several dynamic processes implied in activity analysis. Activity-based approaches are concerned with the analysis of events unfolding over time, and often unfolding over different, but intertwined, time scales. Household and person classifications will change, both as individual households evolve and as all households adapt to changing environmental conditions. We cannot observe Jones' *et. al.* sixth feature without a dynamic framework. Following Hanson and Burnett (1981) and Dix (1981), Lee-Gosselin (1995) recalls the distinction between *expressed choice* and *freedom to act*, and further asserts that "if choice is a process, then understanding behavioural outcomes under constraints requires dynamic measures of freedom to act."

3. TOWARD APPLICATIONS OF ACTIVITY ANALYSIS: THREE PROCESSES OF SCIENTIFIC DEVELOPMENT

We describe here the three processes that underlie the building of an activity analysis framework for forecasting: conceptualization of activity analysis as a set of theoretical constructs, empirical testing and application of those constructs, and the intentional, reflexive interplay between those two processes. We can assign approximate timelines to these processes, but they are not three separate lines. The conceptual development of activity analysis can fairly be said to have been emphasized first, followed by the first empirical tests, and then the first efforts to assess progress, refine theory and formulate new empirical problems. However, these periods do not define distinct epochs, rather they identify three processes that wax and wane in cycles across time. We do not attempt to trace the entire development of activity analysis through these cycles, but rather demonstrate the development of theory, applications and interplay between them by reviewing illustrative developments of each of them.

3.1 CONCEPTUALIZING ACTIVITY ANALYSIS

3.1.1 THE ROOTS OF ACTIVITY ANALYSIS AND THE CONCEPT OF ACTIVITY SPACE

A few studies that we would as classify as activity analysis pre-date Hägerstrand's (e.g., Mitchell and Rapkin, 1954; Chapin, 1965). However, the intellectual roots of activity analysis are found primarily in geographical studies that delineated systems of constraints on activity participation in time-space (Hägerstrand, 1970) or identified patterns of behavior across time and space (Chapin, 1974), and in psychological studies of why people participate in activities and how those motivations are mediated by social structure (Fried *et. al.* 1977).

As analysts looking into households' lives through the often murky window of our survey instruments, we are faced with the question of whether observed routines in household activity choices are behavioral responses to the apparent complexity of all possible activity choices. The realm of all possible activity spaces through which a household might move is, from the observers perspective, quite complex. It was part of Hägerstrand's (1970) admonition that the analyst could construct a more tractable problem by paying attention to people, not the myriad possibilities of the world. He argued for the need to examine spatial relationships as expressions of human behavior and for a set of organizing principals around which to begin such an examination (ibid.). Thus, his *space-time prisms* were the more confined regions of time and place in which a person could exist. Discontinuities of existence in time are not allowed and a person's possible locations in space at one point in time are determined in part by their locations in space at preceding points in time and anticipated locations in the future. Understanding the constraints which form the boundaries of those prisms, we reduce the area of space and time we must search to find the activity schedule the person actually executes, that is, Hägerstrand's *time-space path.*

HOW CONSTRAINTS SEGMENT THE TIME-SPACE PRISM

Central to defining the shapes and sizes of these prisms and the paths through them, Hägerstrand proposed a typology of constraints: capability constraints, coupling constraints, and authority constraints. Capability constraints arise from biological requirements and the tools available to an individual. Some capability constraints, notably biological constraints such as sleep and sustenance, follow the individual throughout their time-space path, but are typically satisfied at a single, home location and require a certain minimum amount of time.

Different travel modes impose different capability constraints on our movement through space and time. Distances between activity locations can be mediated by movement (of people or goods) or communication by either inherent physical abilities or the use of tools. Thus we travel by a combination of certain physical functions and tools—walking, bicycles, buses, autos, etc. We communicate either directly through our senses or by communications technology. Thus the time-space prism through which an individual moves can be divided into regions of varying accessibility, depending on her physical capabilities and the availability to her of different travel and communication tools.

While capability constraints define the limits of our time-space prism, our path inside that prism is determined in large part by coupling and authority constraints. Coupling constraints "define where, when, and for how long, the individual has to join other individuals, tools, and materials in order to produce, consume and transact." (ibid.) To get a haircut, we must arrive at the barber shop during the hours it is open, and if we are particular, on a day our favorite barber is working. Paid employment may require that we interact with other people and tools on a particular schedule at one or more locations. Authority constraints define *domains* within the time-space prism to which an individual either controls the access of other individuals or to which his access is controlled.

Empirical research has shown that household travel can be explained by this framework of constraints. For example, Kitamura, Nishii, and Goulias (1990) show that choices of timing and location for non-work activities by commuters are consistent with a set of hypotheses based on the constraints Hägerstrand proposes. Those authors found that coupling constraints (shop opening times) and authority constraints (work start times) severely limit the number of non-work trips made before work. Because of authority constraints and capability constraints, non-work activities made during work-time are tightly clustered in space around the work location and tend to be either work-related trips or trips to eat. Non-work trips made after work access a wider variety of activities, and though spatially clustered around home, are not as tightly clustered as either before- or during-work trips.

Niemeier and Morita (1995) argue that "work trips" in general should be considered multi-purpose trips since non-work activities are frequently accessed on the trip from work to home (though less so on the trip from home to work). They further show that the differing roles and responsibilities of women and men within households impact relative activity duration for shopping during these trips between work and home. For a given participation by a woman or a man in shopping, the woman is likely to spend more time on the activity. Thus, they also demonstrate how household responsibilities systematically shape the time-space prisms of household members.

TIME-SPACE PRISMS AND HOUSEHOLD ACTIVITY SPACE

Our use of the phrase *activity space* to describe the sets of activities that households access is based on definitions used by Horton and Reynolds (1971) in their initial development of an analytical framework to examine the effects of urban spatial structure on individual behavior. If Hägerstrand defined the limits of the time-space prism; Horton and Reynolds provided additional insight into how households choose paths within the prism.

They defined *objective spatial structures* as the location of a household relative to the objective locations of potential activities and their associated objective levels of attractiveness. By "objective" they mean that relative locations are measured by some standard meter, e.g., changes in degrees of latitude and longitude, applied to all locations. This objective spatial structure contains linear features (e.g., transportation networks, commercial "strips"), nodes (e.g., shopping centers, individual residences or manufacturing plants) and surfaces (e.g., residential population densities). Further, they define a household's *action space* as that group of all locations or nodes within the objective spatial structure about which the household has information and the subjective utility the household associates with those known locations. This subjective utility may be a function of linear features connected to the node (e.g., how accessible is the location by various transportation networks) and surfaces in which the node is embedded (e.g., whether the location is perceived to be located in a safe area). Finally, they define the *household activity space* as the subset of all locations in the action space with which the household has direct contact as the result of day-to-day activities. Thus a household's *activity space* can be described by a set of realized *paths* through Hägerstrand's *time-space prism*. The home location, as the point from which all else in the activity space is perceived, is itself part of the activity space.

Horton and Reynolds go on to postulate a theory of learning that directs activity space formation and change. While a household may reach a point where its activity space remains relatively stable, all that is required to produce a change in the activity space is for the household to add one location to its activity space from its current action space or delete one location from its existing activity space. A change in the action space itself requires learning of a new feature of the objective spatial structure and forming an initial assessment of its subjective utility. Changes in the objective spatial structure typically take place outside the control of a single household. Such changes are typically long-lived additions or removal of nodes (e.g., a new shopping mall), linear features (e.g., a new bus route), and surfaces (e.g., agricultural land newly incorporated into a city for urban development).

3.1.2 ACTIVITIES ACROSS TIME

Very early in its conceptual development, activity analysis focused increased attention of transportation researchers on the dimension of time. Time is conceptualized as being both unidirectional and constant in its flow. We can change the speed and direction we travel through space, but not the speed and direction of either time itself or our movement relative to it; we are unable to stop the flow of time or reverse our course. Therefore, time serves as a different organizing principle for much of human activity than does space. We use time to order activities throughout time periods of different lengths. We progress through time, but do so in socially constructed, as well as "natural" or biologic, periods and cycles. We may schedule today in detail, plan next month, and speculate about next year, all while moving through "life stages" identified by changing household structures, peer and social group memberships, careers and lifestyles.

The incorporation of time into activity analysis remains problematic, in large part because of inadequate conceptualizations of time itself. Prince (1978) observes that while it is sometimes convenient to conceive of time as a "fourth dimension", it is in fact fundamentally different from the spatial dimensions. Among the differences he identifies: we cannot combine temporal and spatial units; there are no time equivalents for area and volume; space is omni-directional while time is conceived to be uni-directional and irreversible. Leach (1966) argues that all concepts of time can be reduced to two basic ideas: uni-directional change and repetition or cycles. Yet this possible simplification ignores that uni-directional change and cycles have both physical and social meanings, which may change depending on the degree of uni-directional change (how far in the past, or how far in the future) and the length of the cycle (from diurnal cycles to the birth and death of succeeding generations.) We should also add that subjective notions of time are not very straightforward either, and vary across cultures.

The lack of a unified conceptualization of time in activity analysis has lead to a variety of treatments of time. Some practitioners treat time as a resource to be allocated; others treat it as a constraint on the allocation of other resources; still others treat travel time as a cost, while simultaneously treating all other time as either a resource or constraint for other, non-travel, activities. Further, activities can be ordered in sequence through time; starting and ending times for activities can be chosen: these choices must often be made simultaneously since many activities cannot overlap in time. Thus activity order and duration are often interrelated choices, that themselves may be affected by past activities and expectations of future ones.

A recent effort to inform the resolution of some of these issues is Pas and Harvey's (1991) review the time use literature. They point out mutual benefits to transportation researchers and time use researchers of a increased interaction between the two fields. Transportation research in general, and activity-based approaches in particular, could benefit from advances in data collection methods and empirical knowledge of household time use; time use research could benefit from the treatment of time use within a spatial context.

Recently, considerable attention has been given to the problem of activity scheduling, which raises questions as to the meanings of time. Many of these questions could be ignored so long as we took an observed activity schedule as given and looked for patterns and regularities in travel associated with that activity schedule. And though there have been several studies of activity choice and activity duration choice (e.g., Hensher and Mannering, 1994), most have been conducted within the context of a single, short time period. That is, activity choice and duration have been studied for the period of (most often) one day, but few of these studies have considered how household planning for other time periods (say, the week) affected the scheduling (activity participation and duration choices) for the day under consideration. Some exceptions are Huff and Hanson (1986) and Pas (1988). The former examined differences in activity participation between daily, weekly and monthly time periods. The latter examined some interactions between daily and weekly travel-activity patterns. Pas hypothesized a two-step process in which weekly behavior is determined first, then conditional choices are made regarding daily travel-activity. His analysis did not reject the hypothesis that socio-economic characteristics of the respondents affected their choices of weekly patterns, but not the conditional choices of daily activities and travel.

3.1.3 THEORIES OF ACTIVITY PARTICIPATION

The activity analysis paradigm has yet to develop or adopt a comprehensive theory of activity participation. The lack of such a theory was not such a problem so long as we were concerned only with problems that took activity schedules as given. Lacking such a theory though, we are unable to assess either motivations for choosing to participate in a given activity or decisions as to when and for how long to engage in an activity. Lacking such a theory, any modeling of the selection and prioritization of activities, that is, any empirical application of activity programming or scheduling models, will be necessarily *ad hoc*.

Chapin (1978) applied a simple theory based on Maslow's "hierarchy of needs" (Maslow, 1970) to his investigation of differences in activity patterns between different socio-economic groups of people. In their application of a "situational approach" to explaining household activity patterns, Brög and Erl (1983) emphasized an individual's subjective evaluations of the "...certain number of options [given] by his environment; this is the objective situation." They caution against expecting that socio-economic variables will account for the situational contexts, and suggest that, to understand behavior, a chain of "objective circumstance—personal perception—subjective situation—individual decision—behavior" must be modeled (Brög and Erl,1980). Tonn (1983a, 1983b) delineated a system of activity participation, but acknowledged he had to draw on an eclectic blend of psychological theories and maxims, none of which he concluded could be regarded as widely accepted. Several analyses of activity participation and duration have employed utility theory—whether strictly interpreted or incorporating some variation, such as satisficing rather than maximizing rules for choices among alternatives. Examples include Adler and Ben-Akiva, 1979; Damm and Lerman, 1981; Kitamura and Kermanshah, 1983; Kitamura, 1984; Kawakami and Isobe, 1986; Recker *et. al.* 1986a, 1986b; and Munshi, 1993.

The choice of this "rational" model has been contested on several counts. Gärling *et. al.* (1993) argue that discrete choice models (a subset of utility-based models) cannot model the interactions between choices or between choosers and that utility models attempt to reduce inherently non-comparable elements of choices to a single scalar. Of these, the more compelling argument is the lack of interaction between choosers (decision makers), especially within the context of activity analysis which explicitly recognizes collections of decision makers (households) as the source of fundamental constraints, resources, and activity participation. Studies from Jones, *et. al.* (1983) to Lee-Gosselin (1990) to Kurani *et. al.* (1994) have demonstrated the role of the household in shaping activity participation and travel.

Bhat and Koppelman (1993) have proposed a framework of individual activity program generation. It views individual's needs as emanating solely from membership within a household. "Subsistence" and "maintenance" activities are viewed as generated by the household. "Leisure" activities are viewed as arising from the needs of each individual. Their proposed structure of household decision making starts with the generation of subsistence and maintenance needs. In the case of subsistence, these needs are measured by the employment status, income, and work hours of the two households heads. The subsequent allocation of subsistence and maintenance activities to household members is mediated by automobile ownership. This allocation serves as input to individual decisions about leisure. One limitation of the framework, as noted by the authors, is that it is restricted to couples and "nuclear" families.

3.2 EMPIRICAL TESTS AND APPLICATIONS

The second process concerns the testing and application of empirical specifications—models—of theoretical constructs. Here, it will be useful to distinguish between two approaches which differ in how travel and activities are linked. We label applications in which travel models function differently for different segments of the study population, depending on differences in the household activity patterns of those segments, as "segmentation" approaches. "Integrated" applications are those in which travel is integrated as a endogenous element of household activity patterns. This distinction is alluded to in a section of Jones' *et. al.* (1990) review on the contributions of activity-based travel research to applied modeling: they distinguish between improved specifications of existing trip-based models and the development of activity based models. They observed that the latter contributions were "much less developed" than the former.

3.2.1 SEGMENTATION APPROACHES

It is our sense that the observation of Jones *et. al.* (ibid.) is still true today. They observed that the application of activity analysis concepts by planning organizations appears to be following a path leading toward adjustments to existing travel demand models through the incorporation of new independent variables, the creation of linked sub-models to incorporate interdependencies (e.g., those caused by the interaction between household members roles and household vehicle availability), and the development of new dependent variables. Another "adjustment" application would be the use of "activity variables" to segment travel demand models, that is to estimate distinct models for different households depending on some measure of activity participation. As noted in the companion paper in this conference by Lawton (1996), since 1990, there has been "a gradual progression in the USA, of expansion of the scope of the (MPO) travel survey and a gradual transformation into a household activity survey," starting with Boston and Los Angeles. The initial stages of this progression favored the segmentation approach. Purvis *et. al.*

(1996) model the effects of work trip duration on non-work trip generation. They estimated separate models to predict two dependent variables: the total number of home-based shop/other trips and home-based social/recreation trips.

3.2.2 INTEGRATED APPROACHES

Activity analysis aspires to provide a framework for analyzing travel demand. Recognizing that travel is derived from activity participation, much of the recent research on activity scheduling is directed at integrating travel into activity participation models. Such an integrated approach would allow for more complex household adaptations to be modeled. To the extent the motivation for improved travel demand forecasting tools is the need to better manage existing facilities, and to the extent that this need is driven by real or potential congestion due to the lack of resources or desire to build new capacity, we are forced to recognize that characteristics of trips affect the formation of activity schedules. A trip based model would not predict increases in evening peak travel due to congestion (an increase in the cost of the trip). An integrated activity/travel model, that includes joint decision making within households, household scheduling of activities and travel outside the evening peak, and other features of activity analysis (discussed below), could explain why individual households would choose an adaptive strategy (e.g., linking a non-work activity to the evening commute trip home) which, when summed across an urban area, results in still greater (or longer lasting) congestion.

We provide examples of empirical tests and applications within two recent areas of investigation—dynamic analysis and household activity scheduling. Our examples form neither an exhaustive nor exclusive list. Again, our examples are few because our aim is to point out a few landmarks and because the other authors at this conference will cover several empirical applications in greater detail. Also, we note that our first class of examples—dynamic analysis—and the specific examples we give—micro-simulation and structural equation systems—do not represent activity analysis, per se. We remind ourselves that it is the conceptual framework, not the analytical tools, that defines activity analysis.

DYNAMIC ANALYSIS

Dynamic analysis is the study of unfolding events over time, and the search for relations in the sequencing, duration and accumulation of events. In an earlier review of activity analysis, Pas (1990) states that "Within the last five years [circa 1985], we entered what undoubtedly will come to be known as the era of dynamic analysis, or as Wrigley (1986) terms it, 'the era of longitudinal data analysis.' " Two approaches toward developing applications of dynamic analyses are *micro-simulation* and *structural equation systems*. We place studies from the latest round of interest in dynamic analysis within our classification of empirical applications because they are largely efforts to develop longitudinal analysis techniques. Wrigley (ibid.) identifies two earlier rounds of interest in longitudinal analysis in the field of human geography. These periods of earlier interest were focused more on conceptual development and data collection methods. In the applications cited below, the data analyzed are from the Dutch National Mobility Panel.

Micro-simulation is distinguished from other empirical applications by the manner in which the aggregation problem is addressed. One stumbling block in the path to forecasting models has been the question of how to aggregate highly detailed household analyses up to representative samples. Micro-simulations generate "synthetic" households who, in aggregate, form a representative sample of the study population at the start time of the simulation. The future travel of these "electron-citizens" is modeled based on their simulated life trajectories. These trajectories can include changes in life stage (or some other socio-economic and demographic measures), residential location, vehicle ownership and other variables.

In MIDAS (Kitamura and Goulias, 1991), a dynamic model of travel behavior is combined with a "demographic accounting system" in which

> "household evolution over time is modelled at two levels, the household and the individual. The building block of the household evolution is the household type transition. Around this transition, household members are made to change education, drivers' license holding, employment, and personal income."

Mobility for each generation (year) of synthetic households is then modeled based on the characteristics of the household in the current generation and their travel (mobility) in their previous generation. This work provides some of the basis and background for the current development of TRANSIMS and AMOS, a micro-simulation model system of daily travel and activity.

Structural equation systems: Golob (1990) describes one application of a model based on a structural equation system. The specific empirical problem he addresses is determining the relationships between income, car ownership, car travel and transit travel as those relationships change over time. Golob describes a structural equation model as:

> "...a specific type of simultaneous equation system in which the variables are divided into two sets—endogenous variables and exogenous variable—and each equation in the system represents the direct effect of one variable upon another variable." (ibid.)

Further, with respect to dynamic analysis,

> "[structural equation] models can incorporate changes over time...of several variables simultaneously, while also including lagged causal relationships between variables." (ibid.) [Ellipses added.]

HOUSEHOLD ACTIVITY SCHEDULING

The development of models of activity scheduling has proceeded through several cycles of theorizing, empirical testing, and reflexion. This development included the design of activity and travel choice models based on the economic theory of utility maximization and subsequent adjustments to these models to reflect information costs and utility satisficing. Most recently, a number of models have been developed around alternative assumptions of human decision making capabilities and processes. These alternatives to utility maximization assume more limited cognitive ability, the use of heuristics (cognitive short cuts), or rule-based decision procedures. The behavioral basis of these models is not in economics, but in cognitive psychology (Simon, 1990; Heath *et. al.* 1994), everyday problem solving (Sinnott, 1989) and artificial intelligence (Hayes-Roth *et. al.* 1979; Hayes-Roth and Hayes-Roth, 1979; McCalla and Schneider, 1979).

Some early models of activity scheduling attempted to make modifications to utility maximizing frameworks in accordance either with activity analysis concepts or alternatives to rational models of human cognitive ability and process. The CARLA model of Jones *et. al.* (1983) identified a subset of feasible alternative schedules according to a system of constraints similar to Hägerstrand's. Root and Recker's (1983) STARCHILD model selected a schedule from all possible schedules based on satisficing, rather than maximizing, rules.

The most recent activity scheduling models are built around the architecture of production systems. For example, Gärling *et. al.* (1989) proposed, and then further described and developed (Gärling, Kwan and Golledge, 1994), a model known as SCHEDULER. It is a production system, described as

> "...a set of rules in the form of condition-action pairs that specify how a task is solved...[it] is also conceived as being realized in a cognitive architecture featuring a perceptual parser, a limited-capacity working memory, a permanent long-term memory, and an effector system" (Gärling, Kwan and Golledge, 1994). [Ellipses added.]

The SCHEDULER framework is limited to individuals' (rather than households') choices of activities, activity duration and departure times, all within a specified period of time.
In another activity scheduling modeling effort, Ettema *et. al.* (1993a) appeal to Simon (1990), (Hayes-Roth and Hayes-Roth, 1979) and Gärling (1993) to argue that production systems represent suitable frameworks for the activity scheduling problem. They do point out that one problem with production systems is the lack of calibration methods and data to estimate and evaluate the efficacy of any given production system in replicating activity scheduling. To overcome the data problem, Ettema *et. al.* (1993b, 1994) develop an interactive, computer program, Method of Activity Guided Information Collection (MAGIC), to collect data on individuals' activity scheduling behavior.

3.3 THE REFLEXIVE NEXUS

The final process we review here are what we have called "reflexions". Two types of these efforts are those that define appropriate contexts and domains for the application of theories and empirical tools, and those that summarize accumulated experience and thinking, link empirical and theoretical advances (and failures to advance), and provide a vision for future development.

3.3.1 DEFINING CONTEXTS AND DOMAINS

Heggie and Jones (1978) wrote one of the early papers within activity analysis that delineated distinct realms with different possibilities for modeling and measurement. Their four domains were defined according to the degree of dependence between decisions along two dimensions: interpersonal and spatio-temporal. The four domains were identified as: (i) independent; (ii) spatio-temporally linked; (iii) inter-personally linked; and (iv) linked on both dimensions. The last two domains were subdivided according to whether the linkages function predominately within or between households. They argued that utility maximizing models of behavior were appropriate for the first domain, of fully independent decisions, but that there were few utility maximizing solutions known for any of the three inter-dependent domains—all of which form the largest part of problems of interest in activity analysis.

Lee-Gosselin (1995) has recently reviewed the realm of interactive data collection methods directed at transport user response in future situations. He distinguishes "stated response" methods from "stated preference" methods and develops a taxonomy of the former which subsumes the latter. The taxonomy is based on the degree to which both constraints and behavioral outcomes are either provided by researchers or elicited from participants. Traditional stated preference work specifies both constraints and behavioral responses (choice sets). Other classes of stated response techniques include "stated tolerance" (behavioral outcomes given, constraints elicited), "stated adaptation" (behavioral outcomes elicited, constraints given) and "stated prospect" (both behavioral outcomes and constraints elicited).

3.3.2 LANDMARK REFLEXIVE EVALUATIONS

The process of developing theories, methods and applications has spawned periodic reviews whose aim went well beyond simply summarizing the record of progress to date. Many of these have attempted to both describe progress and to identify areas in which progress must still be made: particular concepts may have not withstood empirical evaluation; appropriate empirical tools might not have yet been developed; or new concepts had only been recently revealed.

Three such reviews are Jones (1983), Pas (1990), and Jones, Koppelman and Orfeuil (1990). Jones' (1983) early review summarizes the main concepts of activity analysis and provides an assessment the areas of application up to 1983. He develops a typology of six types of potential and actual applications: problem recognition and policy generation, data collection, data analysis, modeling, evaluation, and public participation and policy coordination. He concludes there had generally been significant applications within the first three types, but that applications to modeling, evaluation and public participation and policy coordination lagged. With respect to modeling, Jones identified three areas in which activity analysis could contribute: definition of choice sets, specification of appropriate variables and model structures, and development of new forms of models.

Pas (1990) wrote perhaps the most openly self-conscious reflexion on activity analysis. He wrote

> "It is important...for us to step back every once in a while...to assess what it is we are doing, why we are doing it, and how we are doing it." (ibid.) [Ellipses added.]

The title of his work—"Is travel demand analysis and modeling in the doldrums?"—suggests there was a felt need to address criticisms that recent approaches, including activity analysis, were not progressing rapidly enough toward practical travel demand models. Indeed, he develops a linear history of the subject matter of travel demand analysis and modeling from which the reader might infer that activity analysis was in danger of being supplanted by "dynamic," or longitudinal analysis. Perhaps to counter this impression, he cites Goodwin (1983) who states "...dynamic analyses are inherent to the most rewarding development of activity analysis."

Pas concludes that from a researcher's perspective, travel demand analysis and modeling were not in the doldrums based on the high level of research activity and the number of new ideas generated. However, he does concede

> "...from the point of view of transportation planning practice, it is clear that travel forecasting models have seen little change in recent years. In particular, the activity-based approach has seen little direct application." (ibid.)

The review by Jones, Koppelman and Orfeuil (1990) distinguishes activity analysis from "established procedures," traces methodological developments ranging from data collection to quantitative modeling, describes areas of actual and potential policy applications and provides their perspective on an action agenda. That action agenda is directed toward the two challenges they believe faced activity analysis in the late 1980s: first, to clarify concepts, refine methods and simplify approaches; and second,

> "...to demonstrate the practical usefulness of these approaches, with particular emphasis on the improved ability to understand and predict travel behaviour in a manner which enhances transportation service decision making." (ibid.)

Their assessment of the application of activity analysis to transportation planning mirrors that of Pas and other reviewers. Jones, Koppelman and Orfeuil endorse the conclusions presented by Mahmassani (1988); who in turn summarized those of Kitamura (1988). In short, those conclusions were that the contributions of activity analysis to practical planning tools was limited and fragmentary, activity analysis itself had yet to develop an identifiable and accepted theoretical base, and no clear methodological direction had been charted. What is clear from these reviews at key reflexive moments in the past, is that researchers and practitioners of activity analysis were acutely aware that their aspiration to transform transportation planning tools remained largely unfulfilled. It remains to be seen whether the 1995 New Orleans Conference will provide a landmark reflexive evaluation of a different kind.

4. AN EXAMPLE OF THE THREE PROCESSES AT WORK

The three processes of scientific development and the distinction between segmentation and integration approaches to the treatment of activity analysis and travel demand models provides a framework for examining the overall development and application of the concepts of activity analysis. We cite a series of reports detailing efforts to produce a particular model of activity scheduling to show how those efforts build on processes of scientific development as they have evolved in activity-based approaches; how scheduling models represent one more cycle in our efforts to deepen our understanding of travel demand; and how our desire to develop activity-based forecasting tools is linked to our aspirations for better theory.

The specific example we discuss is work on activity scheduling reported in Ettema *et. al.* (1993a,b; 1994). As a first step in classifying this work, activity scheduling models have attempted to take what we earlier defined as an "integrated" approach: travel is treated as endogenous to the creation of schedules of activities, schedules which when executed (possibly with mid-schedule adjustments) produce observed activity and travel patterns.

Based on models created from both simulated data and data collected through the use of the interactive computer experiments, Ettema *et. al.* conclude that their Simulation Model of Activity Heuristics (SMASH) reacts in plausible fashion to changes in spatial and temporal conditions, produces schedules that contain a high proportion of activities from the agenda of activities to be scheduled, and that schedules tend to be created in order to minimize travel times. Results of the interactive data collection experiment indicate that, within the confines imposed by the program, respondents plan in a fairly simplistic manner. Also, characteristics of activities—their priority on the agenda (the list of all activities that are to be scheduled, if possible, within the current scheduling process), duration, starting times, and ending times—are correlated to the scheduling processes: addition, deletion and substitution and the differential importance of nine schedule attributes. For example, once added to a schedule, high priority activities are less likely to be deleted than are low priority activities. Also, activities that are rescheduled or deleted tend to have shorter duration, earlier start times and less time pressure. Travel time minimization appears to have less effect on the scheduling of activities that are scheduled for earlier in the day than on activities scheduled for later in the day.

We see evidence of the processes of scientific development both in the developments in activity analysis that lead up to of Ettema's *et. al.* work and within their efforts. The behavioral models employed in activity-based applications have moved through cycles of induction-deduction-reflexion that lead from utility maximizing, to adjustments to maximizing (e.g., incorporation of information costs, satisficing), to a variety of non-utility models. In a review of activity scheduling models, Kurani and Kitamura (1996) observe that one advantage of production systems is they can be programmed to model more than one behavior or decision making process. Thus, production systems allow further formulation and testing of theories of decision making.

Ettema's *et. al.* choice of a production system is based on theoretical work spanning Simon (1978), Hayes-Roth and Hayes-Roth (1979), Simon (1990), and Gärling *et. al.* (1993). The interactive data collection revealed a simplified scheduling process. Schedules were built almost solely through additions to the current schedule. Very few deletions or substitutions were made during the scheduling experiments; only after a complete schedule had been articulated were adjustments made to the schedule. This is contrast to the findings of Hayes-Roth and Hayes-Roth (1979) whose work showed a great deal of incremental plan changes. Thus, while building on previous theoretical developments, the divergence of results regarding how activity schedules are constructed between Ettema *et. al.* and the Hayes-Roths suggests a need for continued reflexion, development and testing.

As one example of developments in empirical methods, we refer to our prior discussion of the changes in the treatment of activity duration models, from disaggregate choice models to hazard models (Section 2). Ettema *et. al.* (1995) participated in this development themselves, writing on the application of hazard models to activity choice, timing, sequencing and duration.

5. CONCLUSIONS: PORTENTS OF ACTIVITY-BASED TRAVEL FORECASTING

In writing this interpretation of the development of activity analysis, we have argued that the course of activity analysis can best be traced through three processes: conceptual and theoretical development, empirical testing and application, and the self aware monitoring of the progress and interaction of the first two. This process orientation puts activity-based approaches into a more cyclical, and less linear, historical perspective. We believe this cyclical perspective addresses concerns with the description of the development of activity analysis as linear sequences of distinct epochs raised by Gerardin (1990) in his response to Pas' (1990) review. In particular, Gerardin (1990) argues that "Far from forming a sedimentary evolution, the thirty-five years of research development described by Eric Pas should enrich themselves mutually." He concludes that, "research proceeds in such a way that progress is not linear, but by stop and start."

While we agree with Pas' descriptive history of activity analysis as a series of epochs of distinct emphasis on different problems, we have presented a process oriented history to explain what drives us from one epoch to the next. In contrast to Gerardin, we would describe research as progressing not "by stop and start," but through cycles of induction and deduction, driven by our own monitoring of those cycles and our ability to provide purposive and discursive elaboration both of those cycles and of our awareness of them—or more to the point, of our awareness that we are the purposive agents of those cycles.

In this context, the application of activity-based approaches to travel demand forecasting is not a point in a linear history, nor a layer in a sedimentary history; it is neither a stop nor a start, but one more turn of the wheel. In this conference, itself a reflexive exercise, we may well choose the direction of the next cycle, the pathway we will construct toward activity-based travel forecasting tools. In progressing along that path, we can expect to further elaborate our theories.

One choice that will likely define the direction of that pathway is the choice between making incremental adjustments to existing travel demand forecasting tools or developing activity models in which travel is determined endogenously. In the short term, the incremental approach has the attraction of having already started and of having provided some positive results—it may represent the next turn of the wheel for activity based travel demand forecasting. The perspective we have developed here reminds us though that we should be prepared for the cycles to keep moving. We should be prepared for subsequent cycles, which may well involve a wholesale reformulation of travel demand forecasting into an integrated activity-travel approach in which travel is determined endogenously in activity participation.

Whatever the specific direction, our guess is that applications of activity-based methods will play a major role. And beyond that? If we were to go out on a limb, prospecting into the future and say where the next turn after that may point us, it would have something to do with what we might call "post-modern" models of time-use—models which better represent travelers' propensities to favor predictability or spontaneity.

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1. generate a uniform random number u_{1h} on the range [0,1]. Given u_{1h}, determine x_{1h} from the distribution $P(X_1=x_{1h})$;
2. generate a uniform random number u_{h2}. Given x_{1h} and u_{2h}, determine x_{2h} from the distribution $P(X_2=x_{2h}|x_{1h})$; and
3. generate a uniform random number u_{3h}. Given x_{2h} and u_{3h}, determine x_{3h} from the distribution $P(X_3=x_{3h}|x_{2h})$.

This process is then repeated until all households, each with a specific set of attributes, have been generated.[12] This procedure is conceptually straightforward, easy to implement, and has been used in several models, including Mackett [1985, 1990] and Miller, *et. al.* [1987].

As Wilson and Pownall note, this process implies a causal structure in terms of the order in which the conditional probabilities are computed (i.e., in the assumptions concerning which attributes are conditional upon which others). In practical applications it is not always clear to what extent this conditioning is guided by theoretical considerations as opposed to the availability of a given set of cross tabulations. Alternatively, sufficient redundancy often exists within available census tables that "multiple paths" through these tables may exist, leaving it to the modeler to determine which path is "best" for computing the joint attribute sets (e.g., perhaps one has two-way tabulations of X_1 by X_3 as well as the other two-way tabulations previously assumed; in such a case, which order of conditioning is best?).

More fundamentally, this procedure ignores the potential for significant multi-way correlations among the variables, except for the very limited two-way correlations permitted within the arbitrarily assumed conditional probability structure. This is a potentially serious problem. A recently proposed procedure by Beckman, *et. al.* [1995] for use in TRANSIMS, however, directly addresses this issue.

The TRANSIMS procedure also starts with aggregate census tabulations for each census tract. In addition, however, it utilizes Public Use Microdata Sample (PUMS) files which consist of 5% representative samples of "almost complete" census records for collections of census tracts. Adding up the records in a PUMS provides an estimate of the full multi-way distribution across all attributes for the collection of census tracts. If one assumes that each census tract has the same correlation structure as its associated PUMS, then the PUMS multi-way distribution provides important additional information to the synthesis process. Skipping over a number of important details, primary steps in the TRANSIMS procedure are:

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[12] Wilson and Pownall proposed this algorithm for the case of generating a small sample. In this case "sampling with replacement" (as occurs in the algorithm outlined) is acceptable. If an entire population set is to be generated, then the algorithm shown must be altered so that it involves "sampling without replacement". That is, after each household is drawn, the aggregate household distributions should be modified to reflect the fact that this household has been removed from the distribution, thereby altering slightly the probability distributions for subsequent households.

may be so large and/or sufficiently complex to generate that it might be "just as easy" to work with the entire population.

In trying to build a case for population-based microsimulations, one certainly cannot ignore the computational implications (in terms of both processing time, memory and data storage requirements) of such an approach. This issue is returned to in Section 6. For the moment, the points to note are:

1. the conceptual case for population-based microsimulation does exist, in at least some applications;
2. computing capabilities and costs are continuously improving; and
3. several population-based models are currently under development, the most notable, of course, being the TRANSIMS model [Barrett, *et. al.*, 1995].

The synthesis and updating methods discussed in the following sub-sections do not depend in any significant conceptual way on whether they are operating on a sample or the entire population. For simplicity of discussion, however, the presentations in these sections assume that it is a disaggregated representation of the entire population which is either being synthesized or updated.

4.1 Population Synthesis

All population synthesis methods start with the basic assumption that reliable aggregate information concerning the base year population is available, generally from census data. These data typically come in the form of one-, two- or possibly multi-way tables, as illustrated in Figure 4. Collectively, these tables define the marginal distributions of each attribute of the population of interest (age, sex, income, household size, etc.). In addition any two-way or higher cross tabulations provide information concerning the joint distribution of the variables involved. The full multi-way distribution of the population across the entire set of attributes, however, is not known. The synthesis task, as shown in Figure 4, is to generate a list of individual "population units" (in the case of Figure 4, households) which is statistically consistent with the available aggregate data.

All synthesis procedures developed to date use some form of Monte Carlo simulation to draw a "realization" of the disaggregate population from the aggregate data. At least two general procedures for doing this currently exist. The first appears to have been originally proposed by Wilson and Pownall [1976]. In this method, the marginal and two-way aggregate distributions for a given zone (or census tract) are used sequentially to construct the specific attribute values for a given person (or household, etc.) living in this zone. For example, assume that we are synthesizing households with three attributes, X_1, X_2 and X_3. Also assume that we have the marginal distribution for X_1 (which defines the marginal probabilities $P(X_1=x_1)$ for the various valid values x_1 for this attribute. We also have the joint distributions for X_1 and X_2 and for X_2 and X_3 (which can be used to define the conditional probabilities $P(X_2=x_2|x_1)$ and $P(X_3=x_3|x_2)$. An algorithm for generating specific values (x_{1h}, x_{2h}, x_{3h}) for household h is then:

and Kitamura [1992], for example, used sample households from the Dutch Mobility Panel in their microsimulation model of Dutch household demographics and mobility (MIDAS -- Microanalytic Integrated Demographic Accounting System). Mackett [1985, 1990], as another example, used a 1% sample of households synthesized from more aggregate data in his housing market microsimulation model (MASTER -- Micro-Analytical Simulation of Transport, Employment and Residence).

Situations exist, however, in which it may be useful or even necessary to work with the entire **population** of actors within the microsimulation, rather than a representative sample. At least two major reasons exist for why one might prefer to work at the population level rather than with a sample.

First, situations exist in which computing population totals based on weighted sample results can be difficult to do properly.[11] Consider, for example, the problem of simulating residential mobility. Assume that one is working with a 5% sample of households. Then, on average, each household in the sample will carry a "weight" of 20 in terms of its contribution to the calculation of population totals. If it is determined within the simulation that a given sample household will move from its current zone of residence i to another zone j, does this imply that 20 identical households make the same move? The answer is, probably not. More complex weighting schemes can undoubtedly be devised, but it may prove to be conceptually simpler, more accurate and perhaps even computationally more efficient to deal directly with the residential mobility decisions of **every** household and thereby avoid the weighting problem entirely.

All sample-based models inherently represent a form of aggregation in that each observation in the sample "stands for" or "represents" n actual population members (where, as illustrated above, 1/n is the average sample rate). These n population members will possess at least some heterogeneity and hence variability in behavior. In many applications (microsimulation or otherwise) this "aggregation problem" is negligible, and the efficiency in working with a (small) sample of actors rather than the entire population is obvious. In many other applications, such as the one described above, however, use of a sample may introduce aggregation bias into the forecast unless considerable care (and associated additional computational effort) is taken. In such cases, the relative advantages of the two approaches are far less clear.

Second, as one moves from short-run, small-scale, problem-specific applications (the domain of most activity-based simulation models to date) to longer-run, larger-scale, "general purpose" applications (e.g., testing a wide range of policies within a regional planning context -- presumably an eventual goal of at least some activity-based modeling efforts), the definition of what constitutes a "representative" sample becomes more ambiguous. A sample which is well suited to one policy test or application may not be suitable for another. This is particularly the case when one requires adequate representation spatially (typically by place of residence **and** place of work) as well as socio-economically. In such cases, a "sufficiently generalized" sample

[11] As Mackett [1990] observes, these often involve market simulations in which demand-supply interactions are difficult to deal with on a sample basis.

activity/travel patterns by an activity-based model as a result of the occurrence within the simulation of certain combinations of household needs, constraints, etc.

The importance of emergent behavior within travel demand forecasting is at least two-fold. First, it offers the potential for the development of parsimonious models in the sense that relatively simple (but fundamental) rules of behavior can generate very complex behavior. Second, while all models are to at least some degree "captive" to past behavior through use of historical data to estimate model parameters, the potential for emergent behavior increases the likelihood of the model generating unanticipated outcomes, and hence for "departures from the trend" to occur.

Finally, it may well be the case that microsimulation models will ultimately prove easier to explain or to "sell" to decision-makers relative to more aggregate models. Since microsimulation models are formulated at the level of individual actors (workers, home-owners, parents, etc.), relatively clear and simple "stories" can be told concerning what the model is trying to accomplish (e.g., the model estimates the out-of-home activities which a given household will undertake on a typical weekday, and when and where these activities will occur) to which lay people can readily relate. The technical details of the model's implementation typically will be very complex, but the fundamental conceptual design is, in most cases, surprisingly simple to convey to others.

4. POPULATION SYNTHESIS AND UPDATING

Microsimulation models by definition operate on a set of individual actors whose combined simulated behavior define the system state over time. As discussed in Section 2, in short-run forecasting applications, a representative sample may often exist which can define the set of actors whose behavior is to be simulated (Figure 1). In medium- and long-term forecasting applications, however, even if such a sample exists for the base year of the simulation, this sample can not generally be assumed to remain representative over the forecast time period. As discussed in Sections 2 and 3, in such cases the microsimulation model must be extended to include methods for **updating** the attributes of the set of actors so that they continue to be representative at each point of time within the simulation (Figure 2). In addition, in many applications (particularly larger-scale, "general purpose" regional modeling applications), the base year sample of actors either may not be available or may not be suitable for the task at hand. In such cases, the microsimulation model must also include a procedure for **synthesizing** a suitable base year set of actors as input to the dynamic behavioral simulation portion of the model (Figure 3). Each of these two processes — synthesis and updating — are discussed in the following two subsections.

Before discussing synthesis and updating methods, however, one other important model design issue needs to be addressed. The discussion to this point in the paper has assumed that the set of actors being simulated is a **sample** drawn in an appropriate way from the overall population. This is, indeed, the case in most of the microsimulation models developed to date, including the relatively few medium- to longer-term forecasting models reported in the literature, and regardless of whether the base sample is obtained through survey or synthesis methods. Goulias members. Further assume that there are 1000 traffic zones, three auto ownership levels (e.g., 0, 1, 2+) and five household size categories (e.g., 1, 2, 3, 4, 5+). To save this information in matrix format would require a four-dimensional matrix with a total of $1000 \times 1000 \times 3 \times 5 = 15 \times 10^6$ data items. Also note that a large number of the cells in this matrix will have the value zero, either because they are infeasible (or at least extremely unlikely; e.g., 2+ autos in a one-person household) or because one simply does not observe non-zero values for many cells (as will be the case for many origin-destination (O-D) pairs).

In a list-based approach, one record is created for each worker, with each record containing the worker's residence zone, employment zone, number of household autos and household size. Thus, four data storage locations are required per worker, meaning that as long as there are less than $(15 \times 10^6) \div 4 = 3.75 \times 10^6$ workers in this particular urban area the list-based approach will require less memory (or disk space) than the matrix-based approach to store the same information. Obviously, as the number of worker attributes which need to be stored increases, the relative superiority of the list-based approach increases.

The advantages of list-based data structures for large-scale spatial applications have been recognized for at least twenty years.[7] "Aggregate" urban simulation models such as NBER[8] and CAM[9], both developed in the 1970's used list-based data structures.[10] The key point to be made here with respect to microsimulation is that once one begins to think in list-based terms, the conceptual leap to microsimulation model designs is a relatively small one. Or, turning it around, if one takes a microsimulation approach to model design, efficient list-based data structures quickly emerge as the "natural" way for storing information.

Whether microsimulation possesses other inherent computational advantages relative to more aggregate methods is less clear. Certainly one can advance the proposition that by working at the micro level of the individual decision-maker, relatively simple, clear and computationally efficient models of process can generally be developed. Whether this efficiency in computing each actor's activities translates into overall computation time savings relative to other approaches given the large number of actors being simulated remains to be seen.

A fourth argument in favor of microsimulation is that it raises the possibility of **emergent behavior**, that is of predicting outcomes which are not "hard wired" into the model. Simple examples of emergent behavior of relevance to this discussion might include the generation of single-parent households by a demographic simulator as a result of more fundamental processes dealing with fertility and household formation and dissolution, or the prediction of unexpected

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[7] See, for example, Wilson and Pownall [1976].

[8] Ingram, G.K., *et. al.* [1972].

[9] Birch, *et. al.* [1974].

[10] Conversely, many current commercial travel demand modeling software packages require one to work within a matrix-based data structures -- a restriction which can become more and more inconvenient not to mention computationally burdensome, as one attempts to implement more "behaviorally oriented" procedures within them.

3. WHY MICROSIMULATE?

As briefly discussed in the previous section, a primary motivation for adopting a microsimulation modeling approach is that it may well be the best (and in some cases perhaps the only) way to generate the detailed inputs required by disaggregate models. The strength of the disaggregate modeling approach is in being able to fix decision-makers within explicit choice contexts with respect to:

1. the salient characteristics of the actors involved;
2. the salient characteristics of the choice context (in terms of the options involved, the constraints faced by the actors, etc.) and
3. any context-specific rules of behavior which may apply.

This inherent strength of the disaggregate approach is clearly compromised if one cannot provide adequately detailed inputs to the model. Such compromises occur in at least two forms. One involves using overly aggregate forecast inputs, resulting in likely aggregation biases in the forecasts. The other involves developing more aggregate models in the first place so as to reduce the need for disaggregate forecast input data, thereby building the aggregation bias into the model itself. I believe that a strong case can be made that a primary reason for the relatively slow diffusion of disaggregate modeling methods into travel demand forecasting practice is due to the difficulty practitioners have in generating the disaggregate forecast inputs required by these methods.[3] As described in the previous section, microsimulation in principle eliminates this problem by explicitly generating the detailed inputs required for each actor being simulated.

A second driving force for using microsimulation relates to the **outputs** required from the activity/travel behavior model. Many emerging road network assignment procedures are themselves microsimulation-based (TRANSIMS[4], DYNASMART[5], INTEGRATION[6], etc.) and hence require quite micro-level inputs from the travel forecasting model.

A third point is that, despite the obviously large computational requirements of a large microsimulation model, it is quite possible that microsimulation will prove to be a computationally efficient method for dealing with large-scale forecasting problems. It is certainly the case that a "micro" list-based approach to storing large spatial databases is far more efficient than "aggregate" matrix-based approaches. To illustrate this, consider a very simple example in which one might want to keep track of the number of workers by their place of residence, place of work, number of household automobiles and total number of household

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[3] The only significant disaggregate model used in operational settings today is the disaggregate logit mode choice model. Even in this instance, the number of explanatory socio-economic variables used in the models tends to be relatively limited, presumably due to the input forecasting problem.

[4] Barrett, *et. al.* [1995]

[5] Mahmassani, *et. al.* [1994] and Hu and Mahmassani [1995].

[6] Van Aerde and Yager [1988a, 1988b].

the model. The majority of activity-based microsimulation models developed to date basically fall into this category of short-run, sample enumeration-based models.

Sample enumeration is a very efficient and effective forecasting method **providing**:

1. a representative sample is available;
2. one is undertaking a **short-run** forecast (so that the sample can be assumed to remain representative over the time frame of the forecast); and
3. the sample is appropriate for testing the policy of interest (i.e., the policy applies in a useful way to the sample in question).

Many forecasting situations, however, violate one or more of these conditions. Perhaps most commonly, one is often interested in forecasting over medium to long time periods, during which time the available sample will clearly become unrepresentative (people will age and even die; workers will change jobs and/or residential locations; new workers with different combinations of attributes will join the labor force; etc.). The question then becomes how to properly "update" the sample in order to maintain its representativeness. In other cases, the sample may not be adequate to test a given policy (e.g., it contains too few observations of a particularly important sub-population for the given policy test). If this is the case, how does one "extend" the sample so that a statistically reliable test of the policy can be performed? Finally, their may be cases in which a suitable sample simply does not exist (e.g., perhaps the model has been transferred from another urban area). In such a case, how does one "generate" or **synthesize** a representative sample?

In all of these cases, microsimulation provides a means of overcoming the limitations of the available sample. In the case of the sample becoming less and less representative over time, Figure 2 presents a simple microsimulation framework in which the sample is explicitly updated over time. The behavior predicted at each point in time is then based on a representative sample for that point in time.

If the original sample is either inadequate or missing altogether, then, as shown in Figure 3, an additional step must be inserted into the model, involving **synthesizing** a representative sample from other available (typically more aggregate) data such as census data.

The remainder of this paper provides more detailed discussion of issues and methods associated with Figures 2 and 3. The final point to note at this stage of the discussion is that these figures assume that the disaggregate behavioral model is itself a dynamic one which must be stepped through time (and hence its inclusion within the time loop). Many current activity-based models are fairly static in nature (or incorporate very short-run dynamics, as discussed in Footnote 2). In such cases, the behavioral model can be removed from the time loop and executed only once, using the desired future year sample which has been estimated through the microsimulation procedure. In order to keep the discussion as simple as possible, however, as well as to emphasize what I believe is the need for explicitly dynamic models of urban processes, the "fully dynamic" representation of the process as contained in Figures 2 and 3 is generally used as the basis for discussion throughout the rest of the paper.

The prefix "micro" simply indicates that the simulation model is formulated at the disaggregate or micro level of individual decision-making (or other relevant) units such as individual persons, households and vehicles. A full discussion of the relative merits of disaggregate versus more traditional aggregate modeling methods is beyond the scope of this paper.[1] I believe, however, it is fair to say that a broad consensus exists within the activity/travel demand modeling community that disaggregate modeling methods possess considerable advantages over more aggregate approaches (including minimization of model bias, maximization of model statistical efficiency, improved policy sensitivity, and improved model transferability -- and hence usability within forecasting applications), and that they will continue to be the preferred modeling approach for the foreseeable future. With respect to microsimulation, the relevant question is to what extent does microsimulation represent a feasible and useful mechanism for using disaggregate models within various forecasting applications.

To begin to explore the way in which microsimulation can be used to apply an activity-based model in a forecasting context, first consider the well known short-run policy analysis/forecasting procedure known as sample enumeration. In this procedure, a disaggregate behavioral model of some form has been developed (say, for sake of illustration, an activity-based model which predicts the number of out-of-home activities in which a worker will participate either before or after work, along with the location, duration and trip chaining implications associated with these activities). A representative sample of decision-makers (in this case workers) typically exists, since such a sample is generally required for model development. This sample defines all relevant inputs to the model with respect to the attributes of all the individuals in the sample. The short-run impact of various policies which might be expected to affect activity scheduling and trip chaining can then be tested by "implementing" a given policy, and then using the model to compute the response of each individual to this policy (where, in this case, the response may involve some combination of changes in the number, timing, duration and/or location of out-of-home activities). Summing up the responses of the individuals provides an unbiased estimate of the aggregate "system" response to the policy in question.

Figure 1 very simply summarizes this procedure. This figure can be taken as a very generic representation of a microsimulation process for the case of a short-run forecast, in which all model inputs except those relating to the policy tests of interest are fixed, and hence all that needs to be simulated are the behavioral responses of the sampled decision-makers to the given policy stimuli. Thus, in such cases, "sample enumeration" and "microsimulation" are essentially synonymous, and use of the latter term simply emphasizes the disaggregate, dynamic[2] nature of

[1] For elegant and concise discussions of the rationale for disaggregate models see, among others, Mackett [1990] and Goulias and Kitamura [1992, 1996].

[2] In such cases, the dynamics involved are usually quite short-run (e.g., activity scheduling over the course of a day or perhaps at most a week; short-run dynamic adaption to a new set of constraints/opportunities; etc.), particularly relative to the much longer-term demographic and socio-economic dynamics which are discussed immediately below.

2. WHAT IS MICROSIMULATION?

While many current modeling efforts are microsimulation based, the term itself is rarely defined. **Simulation** generally refers to an approach to modeling systems which possess the following two key characteristics.

1. The system is a **dynamic** one, whose behavior must be explicitly modeled over time.
2. The system's behavior is **complex**. In addition to the dynamic nature of the system (which generally in itself introduces complexity) this complexity typically has many possible sources, including:

   (a) complex decision rules for the individual actors within the system;
   (b) many different types of actors interacting in complex ways;
   (c) system processes which are path dependent (i.e., the future system state depends both on the current system state and explicitly on how the system evolves from this current state over time);
   (d) the system is generally an "open" one in which exogenous "forces" operate on the system over time, thereby affecting the internal behavior of the system; and/or
   (e) significant probabilistic elements (uncertainties) exist in the system, with respect to random variations in exogenous inputs to the system and/or the stochastic nature of endogenous processes at work within the system.

   Note that in speaking of complexity, we are not merely referring to the difficulty in dealing with very large models with large datasets defined over many attributes for hundreds if not thousands of zones. Rather, we are referring to the more fundamental notion of the difficulty in estimating likely future system states given the inherently complex nature of the system's behavioral processes.

Given the system's complexity, closed-form analytical representations of the system are generally not possible, in which case numerical, computer-based algorithms are the only feasible method for generating estimates of future system states. Similarly, given the system's path dependencies and openness to time-varying exogenous factors, system equilibrium generally is not achieved, hence rendering equilibrium-based models inappropriate. In the absence of explicit equilibrium conditions, the future state of the system again generally can only be estimated by explicitly tracing the evolutionary path of the system over time, beginning with current known conditions. Such numerical, computer-based models which trace a system's evolution over time are what we generally refer to as simulation models.

Note that conventional four-stage travel demand models most clearly are **not** simulation models under this definition. Conventional four-stage models are static equilibrium models which predict a path-independent future year end state without concern for either the initial (current) system state or the path traveled by the system from the current to the future year state. Thus in adopting a simulation approach to modeling activity and travel behavior, one is explicitly rejecting the conventional static equilibrium view of urban systems in favor of a dynamic representation of such systems -- a very significant decision, both conceptually and practically.

MICROSIMULATION AND ACTIVITY-BASED FORECASTING

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ABSTRACT

This paper provides an overview of the state of the art of microsimulation modeling applied to activity-based travel forecasting. The paper defines what is meant by microsimulation and discusses why microsimulation might be a preferred approach to activity-based forecasting in many applications. The issue of synthesizing and updating characteristics of the population being simulated is addressed in some detail. Examples of various types of microsimulation models which have been developed to date are provided, including microsimulation models of auto ownership, residential mobility, route choice and network performance, as well as activity-based travel forecasting models *per se*. The paper concludes with a discussion of research and development issues associated with the continuing development of operational microsimulation models. These include: further evaluation of population synthesizing and updating methods; determination of appropriate levels of model disaggregation; establishing appropriate linkages between model components; examination of the statistical properties of microsimulation models; and demonstration of the computational feasibility of these very computer-intensive modeling systems.

1. INTRODUCTION

The purpose of this paper is to provide an overview of microsimulation concepts and methods which are applicable to activity-based travel forecasting.

Including this very brief introductory section, the paper is divided into six sections. Section 2 defines the term microsimulation. Section 3 discusses the reasons why microsimulation may prove useful or even necessary for at least some types of activity-based travel forecasting applications. Section 4 discusses a key step in the microsimulation process -- synthesizing and/or updating the attributes of the population or sample of individuals whose behavior is being simulated. Section 5 then briefly presents several microsimulation models drawn from a range of applications, including activity-based travel forecasting. Finally, Section 6 discusses some of the research and development issues and directions associated with improving the operational applicability of microsimulation methods.

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tool for transportation policy analysis. As noted earlier, efforts are ongoing currently on several fronts to expand the scope of AMOS by incorporating: vehicle transaction and utilization behavior, vehicle allocation, synthetic generation of households and their activity-travel patterns. Planned research activities include the development and incorporation of models for: search termination, activity engagement, time allocation, inter-person interaction, and multi-day behavior.

7. CONCLUSION

This paper has offered an overview of the roles and advantages of the activity-based approach in travel demand forecasting, and discussed requirements for demand forecasting models in current transportation planning contexts. Application examples are presented with two classes of activity-based model systems: more macroscopic structural equations model systems, and micro-simulation model systems. These model systems are in their early stages of development and the examples presented are limited in their scopes. The results presented in this paper have, nevertheless, demonstrated that activity-based model systems are practical tools for policy analysis that overcome the weaknesses of conventional models. The results offer strong support for the development and implementation of full-scale model systems.

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be simply due to the small sample used in the exercise. It is conceivable that the commuters in the sample had very limited alternative commute options and were able to respond within very narrow ranges to whatever TDM scenarios being implemented. Whether this observation can be generalized or not needs to be determined in the future by the analysis of full data set.

Table 10
AMOS Simulation Results: Congestion Pricing (TDM #5)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	43.0%	64.4%	35.6%	36.5%
Non-Work	57.0%	35.6%	64.4%	63.5%
TRAVEL MODE				
Auto - Driver	50.2%	56.3%	51.9%	39.7%
Auto - Passenger	17.0%	10.3%	18.3%	22.2%
Other	32.8%	33.4%	29.8%	38.1%
TRIP DURATION (min.)				
Total	19.0	23.0	22.6	13.5
Auto-Driver	21.4	23.5	24.5	16.1
Auto-Passenger	17.3	16.4	21.8	14.5
Other	16.2	24.2	19.9	10.2
HOT STARTS (%)	36.8%	34.5%	36.5%	34.9%
PERCENT OF TRIPS	100%	26.9%	32.2%	39.0%
TRIPS PER PERSON	3.30			

Another possibility is that the Response Option Generator has not been fine-tuned enough to be able to detect possibly minute differences in commuters' responses to different TDM measures. In particular, the results suggest that a neural network be developed for each TDM measure separately.[17] The invariance in simulation results across the TDM scenarios may also be due to the limitations of the prototype used for the analysis. For example, destination choice has not been implemented in the prototype. In addition, the simplistic evaluation and acceptance rules adopted in the prototype may have resulted in premature search termination for each commuter, possibly leading to the acceptance of the baseline patterns with a higher probability than it should receive.

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

[17] In the prototype used in this study, the neural network is designed to be able to handle all TDM scenarios examined.

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

Table 9

AMOS Simulation Results: Parking Pricing (TDM #1)

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

Congestion Pricing (TDM #5): The results with congestion pricing at a level of $0.50 per mile with 30% reduction in travel time are summarized in Table 10. The fraction of auto trips, 50.2%, is higher with this TDM than with parking pricing (47.5%), but is lower than the baseline result (54.0%). Notable is the result that the reduction from the baseline in driver trips in PM peak is much smaller than that in the morning peak. Other than mode shares, the results of this TDM are very similar to those of TDM #1.

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

The results may seem less encouraging from transportation policy viewpoints, however, because the effects of the TDM scenarios examined here are small, and because there are only a few discernible differences among the impacts of the respective TDM scenarios. These results may

The results of the analysis are summarized for TDM #1 and TDM #5 in Tables 8 through 10. The reader is cautioned that the number of sample households from the MWCOG data base that were available to the study was unfortunately very small and the results presented here are subject to sampling errors.[16] It must also be noted that this exercise has been made for illustrative purposes and the size of the sample used here, and some of the simplifying assumptions existent in the prototype, warrant neither generalization of the results obtained nor general assessment of the relative effectiveness of the TDM scenarios examined here.

Table 8
Baseline Travel Characteristics

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

Baseline: The distribution of trip purposes (work vs. non-work), travel mode (auto-driver, auto-passenger, other), mean trip duration by mode, percent of hot starts, and average number of trips per person are summarized in Table 8 for AM peak, PM peak and off-peak periods. Slightly over 60% of the trips are work trips (including trips from work to home), with higher fractions during the morning and afternoon peaks. Overall over three-quarters of the trips are made by auto. The large fraction of trips by "other" mode in the afternoon peak period represents walk trips made in this period by this sample of commuters.

Parking Pricing (TDM #1): Results of simulation runs with TDM #1, parking pricing with a surcharge of $8 a day, are summarized in Table 9 The most notable change is in modal split. The fraction of auto driver trips decreased from 54.0% in the baseline case to 47.5%, and auto passenger trips from 18.4% to 16.4%. The fraction of "other" modes increased by 7.8% during AM peak, 6.3% in the PM peak and 4.4% during off-peak periods, respectively.

[16] In the future the spatial and temporal resolution of micro-simulation results can be refined by using more households, possibly synthetic households distributed over the study area.

Results of the TDM stated-adaptation section were used to train the neural network in the Response Option Generator. The resulting network consists of 45 input nodes, 8 output nodes, and two hidden layers. The input nodes may be grouped as: personal and household attributes, work schedule characteristics, commute characteristics, trip chaining characteristics, mode characteristics, and TDM scenarios. The eight output nodes comprise: change departure time, use transit to work, ride-share to work, ride bicycle to work, walk to work, work at home, do nothing different, and other (long-term responses treated as doing nothing in short-term policy analysis).

Table 7

TDM Measures Included in the AMOS Survey in the Washington, DC, Metropolitan Area

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

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

6.2.4 Simulation Results

Using the AMOS prototype described above, the effectiveness of the following TDM measures are evaluated:

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

A total of 20 simulation runs were performed for each TDM measure.

and timing of activities. Using the time utility concept, AMOS evaluates TDM measures while considering their impacts on the entire daily activity, not just on the commute trips which these measures often target.

Acceptance Routine compares the activity-travel patterns so far generated, and determines whether the search should continue or one of the patterns so far generated should be adopted. The routine represents the assumption that, based on the outcomes so far, the individual forms a subjective distribution of utilities associated with alternative patterns; assesses the likelihood of obtaining a better activity-travel pattern; and terminates the search when the cost of search exceeds the expected gain of searching further. Experiments are being designed to validate this theoretical search termination model and to estimate the parameters.

The output of the AMOS micro-simulation is modified and accepted travel patterns that represent individuals' responses to TDM measures.

6.2.3 AMOS Survey

A prototype of AMOS has been developed and implemented in the Washington, DC, metropolitan area. The implementation effort adopts the Metropolitan Washington Council of Governments (MWCOG) traffic analysis zone (TAZ) system and zone-to-zone network travel time matrices by travel mode. Network skim data are available for: drive alone (SOV), ride-sharing (HOV), public transit with walk access, and public transit with auto access. Travel times by bicycle and walk are estimated by applying assumed speeds (6.5 mph and 2.5 mph, respectively) to the centroid-to-centroid distance. The implementation effort thus utilizes as much spatial and modal information as available from the MWCOG data base.[15]

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

In the survey, respondents were given a description of a TDM measure, then asked in an open-ended format, "What would you do?" if the measure had been in fact implemented. Commute travel time and other pertinent parameters were customized such that the hypothetical scenario would closely represent each respondent's commute situation. Follow-on questions were asked to probe into details of the stated behavioral adjustment (e.g., how to drop off a child at the day-care when public transit is used to commute). The TDM measures included in the survey are described in Table 7.

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[15] Note that travel time data used are *static*; possible changes in network service levels due to TDM measures are *not* reflected in the simulation.

and all necessary secondary and tertiary changes are made while considering a rule-base that represents a series of constraints and tendencies, including Hägerstrand's coupling constraints. Then the resulting modified pattern is evaluated against those patterns that have so far been generated, and is accepted when a set of rules is met. AMOS thus replicates an individual's trial-and-error search behavior for a better travel pattern based on the paradigm of satisficing. The structure and functioning of the model system is illustrated below by briefly describing each model component.

Baseline Activity-Travel Pattern Analyzer inspects "base-line" travel diary data and determines whether the diary data under consideration are complete, with all trips and pertinent information intact. It also checks whether the sample individual and/or her travel pattern falls in the categories targeted for analysis. Another major function it performs is to develop indicators of travel pattern characteristics (e.g., there is a stop during the commute trip) that feed into the Response Option Generator described next.

Response Option Generator is a key stochastic element of AMOS that produces response patterns to a change in the travel environment. The input to the Generator consists of: household and person attributes, network and land use characteristics, characteristics of the change in the travel environment (e.g., TDM attributes), and the indicators of the baseline activity-travel pattern characteristics prepared by the Analyzer. Given these, the Generator simulates how the sample individual response to the TDM measure.

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

Activity-Travel Pattern Modifier examines the baseline pattern and, if the response option from the Generator necessitates it, performs: (i) activity re-sequencing (re-arrangement of the order in which out-of-home stops are made), (ii) activity re-linking (re-combining of out-of-home stops into trip chains), (iii) mode and destination assignment, and (iv) trip timing adjustment. Such adjustments are needed primarily when a travel mode change or a departure time change implied by the response option, makes the baseline pattern infeasible or impractical. The Modifier then examines the feasibility of the resulting modified activity-travel pattern using a rule base.

Evaluation Routine assigns a utility measure to the modified activity-travel pattern using time-use utility functions (see RDC, 1993; Kitamura *et. al.*, 1995b). The attractiveness of the pattern produced by the Modifier is measured in terms of the utility generated by allocating time to, and engaging in, the in-home and out-of-home activities contained in the pattern. The utility functions have been developed using the time-use data obtained from the time-use survey conducted as part of the implementation study. The ongoing effort includes the generalization of the utility functions to include non-time elements such as mode attributes, monetary expenses, mode choice model is not differentiated by trip purpose as noted earlier. The model system does not yet have the capability to endogenously generate fixed activities. There are many areas where development, extension and refinement are needed. Nevertheless it can be concluded that the study has demonstrated that activity-travel behavior in time-space prisms can be simulated reasonably well and that travelers' responses to changes in travel time or work schedules can be examined using the micro-simulation model system. The PCATS model system is readily applicable to other types of scenarios, such as changes in store hours or extended operating hours of public transit, which are difficult to address with the conventional trip-based models that do not incorporate the time dimension and disregard time-space constraints. An additional future task is to incorporate into PCATS the behavioral mechanism for activity engagement. The "utility-maximizing," nested-logit model of activity type choice incorporated in PCATS captures the salient tendencies associated with activity type choice; it, however, hardly captures the reason for activity engagement. Effort is ongoing toward the development of a model of activity engagement which represents the motivations for activity engagement and which will make PCATS truly behavioral.

6.2 AMOS

Activity-Mobility Simulator (AMOS) is a micro-simulation model system of individuals' adaptation behavior which predicts changes in travel behavior that will follow a change in the travel environment. The individual's adaptation behavior is characterized as a trial-and-error experimentation process. The development of AMOS has been motivated by the recognition that the traditional, trip-based, four-step procedures are incapable of incorporating TDM and other policy measures that are now the primary focus of urban transportation planning.

A prototype of AMOS has been developed and implemented in the Washington, D.C., metropolitan for the evaluation of selected TDM measures. AMOS is currently being implemented in three major metropolitan areas of California. In this implementation, AMOS is being combined with: a household vehicle transactions model which predicts the timing and type (addition, replacement, or disposal) of vehicle transactions and the types of acquired vehicles; and a demographic simulator which predicts the evolution of demographic and socio-economic attributes of households. AMOS will thus serve as a long-term forecasting model. Detailed discussions of AMOS can be found in RDC (1995), Kitamura *et. al.* (1993, 1995a) and Pendyala *et. al.* (1995). The description of the AMOS components below draws from Kitamura *et. al.* (1995a).

6.2.1 AMOS Components

AMOS comprises five main components and a reporting routine. In a nutshell, it functions as follows. First, how an individual may respond to a change in the travel environment caused by, say, a TDM measure, is determined by Monte Carlo simulation with a neural network that has been calibrated using results of a stated-response survey designed and administered for AMOS calibration. The individual's "base-line" travel pattern is then modified based on the response, tendencies are not found for the W-H-O-H pattern, however. Yet, it is cautioned that the frequency of out-of-home activity engagement is small in the simulation results and the statistics presented under the W-O-H and W-H-O-H patterns contain large variations.

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

This scenario analysis has demonstrated that PCATS facilitates the analysis of time-oriented policies such as changes in work schedules while explicitly considering time-space constraints in the analysis. PCATS also represents the repercussions of a change in the travel environment, including induced (or suppressed) travel and changes in activity location and duration.

Table 6

Results of Scenario Simulation with a Sample Individual

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

1 W-H: work → home. W-O-H: work → other → home. W-H-O-H: work → home → other → home

2 In minutes. Out-of-home time excludes travel time.

3 Since static travel time is used in the simulation, there is no random element in travel time (and therefore in in-home time) for the first travel pattern, "W-H," where the individual returns home immediately after work and engages in no out-of-home activity.

Yet, PCATS is still in its early stage of development; it would be more appropriate to say the model system as presented in this study is an initial prototype. For example, the destination-correlation coefficients. The results point to possible deficiencies in the model components, especially the activity type choice models. The results, nevertheless, demonstrate that the simulation system can replicate the observation reasonably well, at least with respect to total travel time, in-home flexible activity duration, and number of trips.

6.1.3 Scenario Analysis

PCATS is now applied to assess how changes in the travel environment affect an individual's activity and travel. In this analysis a sample individual is selected and his activity and travel after work is simulated for each of the scenarios shown in Table 5.

Table 5
Scenarios Used in the Simulation Analysis

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

The sample individual's profiles are as follows:

An employed male of 54 years old;
household income in the 1,500,000 to 2,000,000 yen range
has held a driver's license for 30 years;
one vehicle available to the household;
commutes to CBD Osaka;
lives approximately 30 km to the south from Osaka along the Osaka Bay; and
has good freeway access to the Osaka CBD.

The individual is assumed to be at the work location when work ends (which is assumed to be the ending point of a blocked period), and the next blocked period is assumed to begin at midnight. It is thus assumed that the entire evening period, after work till midnight, is an uncommitted block of time. Table 6 summarizes the results obtained by performing 100 simulation runs.

The frequency of the simple W-H pattern increases from 84 in the base case to 91, 89 and 90, respectively, in the three scenarios. Quite notable in Scenario 1, where work ending time is moved to 6:00 PM, is the substantial reduction in the out-of-home activity duration and the slight reduction in the travel time associated with the W-O-H pattern. The in-home activity time does not show very much change. The shortening of the after-work open period caused by the change in work ending time has prompted the individual to engage in out-of-home activities less frequently. When the W-O-H pattern is engaged, the activity location is closer and the activity duration is much shorter, presumably to accommodate the tighter time constraints. These

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

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

6.1.2 Validation

A validation analysis is conducted to determine how well the simulation system replicates observed activity and travel patterns. In the analysis, expected values obtained from the simulation are compared against observed values for several indicators of activity-travel patterns. Expected values are obtained by averaging the results of 100 simulation runs performed for each sample individual. The results of the validation study are summarized in Table 4 for 374 sample individuals whose activity records are complete.

Table 4
Results of the Validation Study

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

S.D.: standard deviation across sample individuals

t: t-statistics associated with the difference between the predicted and observed values (not based on the standard deviations associated with "predicted" values)

R^2: Pearson correlation coefficient between predicted and observed values

It can be seen from Table 4 that total travel time, in-home flexible activity duration, and number of trips are relatively well represented by the simulation. According to the t-statistics, however, predicted values and observed values are significantly different for all indicators (at $\alpha = 0.05$). In particular, number of non-work destinations and number of non-work trip chains have very small activity type, assuming that the parameters of the distribution (the mean and a shape parameter) is a function of personal attributes and other explanatory variables. Weibull distributions are exclusively used in the current version of PCATS.[14] The explanatory variables used in the duration models are: person and household attributes, past activity engagement, time of day, time availability and location type indicator. The location types used here are {home, non-home}. For detailed descriptions of model estimation results, see can be found in Otsuka (1996).

The Activity Type Choice Model developed here has a two-tier structure, and is formulated as a nested-logit model. In the first (upper) tier, one of the following three broad classes of activities is chosen: in-home activity, activity at (or near) the location of the next fixed activity, and general out-of-home activity. Exactly which alternatives can be included in the choice set is determined considering prism constraints. In other words, the formation of choice sets in PCATS simulation is governed in part by prism constraints. The second tier under "in-home activity" includes: engage in out-of-home activity subsequently, and do not engage in out-of-home activity within the current open period. If the former is the case, then the duration of the in-home activity will be determined, and the activity choice model will be applied again with the "in-home activity" alternative excluded from the choice set. If the latter is the case, then the travel to the location of the next fixed activity will be simulated. Likewise, if the option of "activity at (or near) the location of the next fixed activity" is selected in the first tier, then the travel to the next fixed location will be simulated.

If "general out-of-home activity" is chosen, then the activity type is selected in the second tier. Activities are classified into the following six activity types, which comprise the choice set in the second tier: meal, social, grocery shopping, comparison shopping, hobbies and entertainment, and sports and exercises. The explanatory variables used to model the choice of out-of-home activity type include: personal attributes: age, sex, home-maker or not, time of day, and probability that the activity duration fits within the open period.

The Destination and Mode Choice Model is formulated also as a nested-logit model. The first tier concerns the choice of destination, and the second tier the conditional choice of travel mode, given the destination. In the current version of PCATS, one model is applied to all trips; this is restrictive and in the future models will be differentiated by trip purpose. Municipalities are used as the unit of geographical aggregation in this study. Travel modes are classified as {public transit, automobile, bicycle, walk}. The explanatory variables used to account for destination choice are: zonal population, the number of commercial establishments, intra-zone destination dummy, the possible minimum travel time to the destination zone then to the location of the next fixed activity, and the probability that the provisional activity duration fits within the open period given the activity is pursued at the destination zone. The explanatory variables for conditional mode choice, given a destination are: age, sex, employment status, driver's license holding, household income, number of vehicles available, time of day, travel time and cost by mode, and number of transfers, intra-zone trip dummy, and location type indicator (indicators of the combination of the current location type and the location of the next fixed activity).

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[14] This is not to exclude the possibility that in the future more suitable distribution functions may be identified and used in PCATS.

those pursued in an open period shall be called *flexible activities*.[12] Given the speed of travel, the ending time and location of a blocked period and the beginning time and location of the subsequent blocked period, define a time-space prism in which the individual's activity and travel are contained. It is assumed that the individual makes activity engagement and travel decisions at the beginning of each open period and also when an activity is completed within a open period. It is thus assumed that activity engagement decision is made sequentially, conditioned upon past activity engagement.

6.1.1 Outline of PCATS

PCATS is based on a sequential decomposition of the probability associated with an activity-travel pattern, namely,

$$Pr[A, B, C, ...] = Pr[A]Pr[B|A]Pr[C|A, B] ....$$

where A, B, C, ... refer to events brought about by activity-travel decisions, e.g., leave for work at 6:30 A.M. by car. Using this sequential decomposition rule, the multiple decisions underlying an activity-travel pattern can be expressed by a product of probablistic elements, each associated with an activity episode or trip. Furthermore, each of these probablistic element can be further decomposed into conditional probabilities associated with respective aspects of activity-travel decision, e.g., activity type, activity duration, location, and travel mode (if relevant). Now, there are alternative sequences of decomposition that are equivalent, e.g.,

$$Pr[A, B, C] = Pr[A]Pr[B|A]Pr[C|A, B] = Pr[B]Pr[C|B]Pr[A|B, C] = ...$$

Then a particular sequence may be preferred and selected considering: theoretical support, policy sensitivity, and ease of modeling. The sequence adopted in the development of PCATS can be depicted as: activity type → location → travel mode → activity duration.

Activity Duration Models are first discussed because they are used in the activity type choice model presented next.[13] The distribution of durations of flexible activities is determined by

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

[13] For earlier studies on the subject, see Mannering (1993), Niemeier and Morita (1996), Bhat (1996a, 1996b), Ettema *et. al.* (1995) and Kitamura, van der Hoorn & van Wijk (1995).

6. MICRO-SIMULATION APPROACH TO ACTIVITY-BASED DEMAND FORECASTING

The second approach is the micro-simulation of activity engagement and trip making. Several model systems that have been developed attempt to represent the cognitive processes that accompany activity scheduling and trip planning. These developments reflect advances made in models of human cognition, decision making and problem solving. For reviews of developments in activity scheduling, see Axhausen and Gärling (1992) and Gärling *et. al.* (1994).

Preceding the current efforts to develop models of activity scheduling is CARLA (Jones *et. al.*, 1983), which is a model system that identifies feasible alternative schedules from all possible schedules by applying systems of constraints. STARCHILD (Root & Recker, 1983; Recker *et. al.*, 1986a, b) is a model system where activity-travel behavior is conceptualized as the choice of a particular schedule from all possible schedules based on utility measures. Following these predecessors are *computational process models* that describe how people formulate and execute schedules. As the name indicates, the computational process approach focuses on the process of decision making and captures heuristics and short-cuts that are involved, as opposed to assuming overriding behavioral paradigms such as utility maximization. One example of computational process models is the *production model* (Newell & Simon, 1972), which is a model of human problem solving comprising a set of rules, or condition-action pairs that specify an action to be executed when a condition is encountered. Several computational process models of activity scheduling have so far been developed, including: SCHEDULER (Gärling *et. al.*, 1989, 1994), SMASH (Ettema *et. al.*, 1993, 1994), DynaMIT (Tasker and Axhausen, 1994), and the framework presented in Vause (1995). These model systems are reviewed in detail in Kurani and Kitamura (1996). The discussions in the rest of this section are concerned with AMOS (Kitamura *et. al.*, 1993, 1995a, 1996; Pendyala *et. al.*, 1995), and PCATS (Kitamura, Fujii & Otsuka, 1996; Kitamura and Fujii, 1996), which have been applied to produce forecasts.[11]

6.1 PCATS

PCATS simulates the individual's activity engagement and travel within Hägerstrand's prisms. In defining prisms for each individual, it is assumed that the simulation period, say a day, can be divided into periods of two type: *open periods* and *blocked periods*. Open periods are ones in which the individual has the option of traveling and engaging in activities. Blocked periods, on the other hand, are ones where the individual has committed to engage in certain activities at certain locations. Activities participated within a blocked period shall be called *fixed activities*;

[11] The discussions in the rest of Section 6 are excerpts from Kitamura and Fujii (1996).

Table 3
Effects of Travel Time Reduction on Activity Engagement and Time-Use Utility

	Base Case		Strategy 1		Strategy 2	
	No Stop	Stop	No Stop	Stop	No Stop	Stop
Discretionary out-of-home time (hr.)	0.000	0.902	0.000	0.975	0.000	0.902
Travel time (hr.)	1.000	1.500	1.000	1.250	0.875	1.500
In-home time (hr.)	5.000	3.597	5.000	3.775	5.125	3.597
Time returned home	19:00	20:24	19:00	20:14	18:53	20:24
Probability of choice	0.538	0.462	0.497	0.503	0.562	0.438
Expected time use utility	0.290	0.138	0.290	0.303	0.389	0.138

In the case a stop is made on the way home, the 15-min. travel time reduction between work and activity center under Strategy 1 results in an increase in out-of-home activity time by 0.073 hr. (4.3 min.), which is about 30% of the travel time saving. The remaining 10.7 min. is assigned to in-home activities. The utility associated with the pattern with a stop increases from 0.138 to 0.303, with the choice probability increasing from 0.462 to 0.503. Likewise, it can be seen that the utility of the pattern without a stop increases from 0.290 to 0.389 under Strategy 2 where the travel time between work and home is reduced by 7.5 min. The conventional unconditional expected representative utility (denoted as "E[V]") and the expected representative utility of a pattern given that the pattern is chosen ("$\ln\sum e^V$"), are shown below for these three cases:[10]

	E[V]	$\ln\sum e^V$
Base case	0.220	0.910
Strategy 1 (improvement between work and activity center)	0.297	0.990
Strategy 2 (improvement between work and home)	0.279	0.964

It can be seen that Strategy 1, which involves the improvement of travel time between work and activity center, produces a larger expected utility than Strategy 2. Consistent with this, the representative utility of a chosen pattern reveals that Strategy 1 in fact would offer more benefit.

The analysis of this example is limited in the sense that only two simple alternative activity-travel patterns are considered for just one person. The results have nonetheless shown that the model system can be used to evaluate transportation planning options while considering changes in utilities associated with activity-travel patterns.

[10] The discussion here is based on the assumption of the logit model of discrete choice that the perceived utility of an alternative, say j, can be expressed as $U_j = V_j + \epsilon_j$, where V_j is the "representative utility" and ϵ_j is an error term with an extreme-value distribution. Because the utility measures that can be identified from the analysis here are relative measures, E[V] and $\ln\sum e^V$ are not comparable to each other.

Table 2
Effects of Commute Time Reduction on Time Use and Travel

	Base Case	10-min. Reduction	Difference
Total out-of-home activity duration	25.56	27.44	+1.88
Increase in travel time	6.78	7.14	+0.36
Frequency of home-based trip chains	0.03	0.04	+0.01
Total time spent at home	216.1	223.2	+7.11

5.2 Example II: Time Use Utility

In another modeling effort an attempt is made to formulate the utility of daily activities. The utility of an activity is assumed to be the function of the time allocated to it and the attributes of the individual. The coefficients of the utility function are specified as linear functions of subjective preference ratings given by the respondent for respective types of activity.

The resulting model system is applied in this example to evaluate alternative improvement strategies by estimating how travel time reductions they produce may affect the daily utility. Consider a simple network which encompasses the home base, the work base and an activity center. In the base case, the travel time between home and work is 1 hr., that between work and the activity center is 30 min., and that between the activity center and home is 1 hr. Consider the following two improvement strategies:

Strategy 1: reduce the travel time between work and activity center by 15 min.
Strategy 2: reduce the travel time between work and home by 7.5 min., one way

Suppose work ends at 6:00 PM, and the commuter may choose to make a stop for discretionary activity on the way home at the activity center. The impacts of the two strategies on the activity and travel of a hypothetical person are estimated for the activity and travel of the commuter after work, and are summarized in Table 3 for the case where no stop is made and the case where a stop is made. Along with the amount of time allocated to out-of-home discretionary activities, travel time, and in-home activity time, the table shows the probability that an out-of-home discretionary activity will be pursued on the way home, and the expected utility associated with the activity pattern.

5.1 Example I: Evaluation of Induced Trips

The first example is based on a structural equations model system of commuters' time use and travel after work.[9] The data used in the study were collected in 1994 as part of an evaluation study of the impact of new Wangan (Bayshore) Line of the Hanshin Expressway system in the Osaka-Kobe metropolitan area. The survey adopted self-administered mail-out, mail-back questionnaires, which were distributed to 4,714 households along the Wangan Line and several competing routes. Usable responses were obtained from 1,257 individuals of at least 16 years old, in 594 households (response rate of 12.6%). A one-day activity diary was included in the survey instruments. The diary collected, for each activity, information on: the activity type, beginning time, ending time, facility type, type of accompanying person(s), spatial fixity, and temporal fixity. For each trip, information was collected on: travel mode, departure time, arrival time and number of accompanying persons.

The structural equation model system of mobility and time use included as its endogenous variables:

- number of trips after work and before returning home for the first time,
- total out-of-home activity duration (excluding travel) after work and before returning home for the first time,
- increase in travel time due to trips made to engage in out-of-home activities after work and before returning home for the first time,
- frequency of home-based trip chains after returning home for the first time till retiring for the day, and
- total time spent at home after returning home for the first time till retiring for the day.

The exogenous variables include: commute duration, regular work starting time, regular work ending time, flexible work hours, number of hours overworked, age, work trip mode, number of restaurants in work zone, preference indicator for out-of-home activities, and preference indicator for in-home activities.

The estimated model system was used to estimate the impacts of a 10-min. reduction in commute time on time use and travel. The results are summarized in Table 2. The model system indicates that the 10-min. travel time saving will lead to an increase in the average total out-of-home activity duration by 1.88 min. and an increase in the total time spent in home by 7.11 min. The average total travel time increases by 0.36 min. Over 70% of the time saved is applied to additional in-home activities, and about 19% to out-of-home activities. The results here indicate that a relatively small number of trips are induced by travel time savings of the magnitude analyzed here, and that much of the travel time saved is spent at home.

[9] For time use analysis in transportation planning in general, see Pas and Harvey (1991). Examples of empirical studies can be found in Kitamura *et. al.* (1992, 1995b).

'other' activities," and discretionary activities include "other types of shopping, eating out, and visit/social/sport." Sex, income, presence of children, marital status, occupation and home ownership are used as exogenous variables. In addition, the following set of mode use indicators is developed and used as exogenous, segmentation variables in the model: "exclusively car," "car + walking or bicycling only," "car + public transport," and "exclusively mode(s) other than car." Model coefficients are estimated by segment while constraining selected coefficients to be common among subsets (or the entire set) of the segments. This is equivalent as incorporating interaction terms that consist of combinations of an exogenous variable and one of the segmentation variables. Based on the results of model estimation, observations are made as to how the exogenous variables are differently associated with the endogenous variables across the mode use groups. Golob and McNally (1996) have further extended the analytical scope by including inter-personal interactions.

These structural equations models have offered insights into the relationship among activity engagement (often expressed in terms of time allocation) and travel. These model systems, however, offer no explicit treatment of the decision mechanisms underlying activity engagement. They represent a translation of a set of hypotheses into a system of simultaneous equations that involve "causal" links, such as "income affects expenditure," that are expressed as linear equations of (latent) endogenous and exogenous variables. This limits the richness of the behavioral theories that can be incorporated into the model system; relationships derived from theoretical considerations must be simplified to the form, "A affects B." In addition, no structural equations models have been developed where constraints on behavior (e.g., the total time available is limited to 24 hours per day) are explicitly introduced. Consequently care must be exercised when applying these models in cases where extrapolation beyond the relationships embedded in the estimation data set, is involved. Another limitation is that structural equations models can represent multinomial choices only approximately. In terms of travel demand forecasting, the models developed so far adopt aggregate representation of travel demand (e.g., total number of trips, travel time expenditure by trip purpose, or total VMT), and therefore do not support the analysis of travel demand where the spatial and temporal dimensions become critical, such as traffic congestion, pollutant emissions, and evaluation of congestion pricing.

Structural equations models nevertheless constitute a powerful approach to the analysis of travel demand. In particular, it facilitate expeditious exploration of alternative behavioral hypotheses and development of quantitative model systems of activity and travel that are capable of offering results that cannot be produced with the conventional model system. This can be seen in the two application examples presented below.[8]

[8] The discussions in the rest of Section 5 draw from Kitamura, Pas and Fujii (1996).

- *Temporal variations*: It is required that variations in travel demand from day-to-day,[7] between weekdays and weekend, and across seasons be represented. For the purposes of emissions analysis, it is desired that the annual distribution of link traffic volumes be estimated.

- *Trip Attributes*: Travel demand must be forecast in terms of link travel volume by mode by time of day. As indicated in Table 1, emissions analysis using currently available emissions models requires that vehicle-miles traveled, average speed, fractions of hot and cold starts, and vehicle mix be forecast by small geographical area (grid). If these macroscopic indicators of travel demand are to be forecast by aggregating the attributes of individual trips, then vehicle type and hot/cold start must be determined as trip attributes in addition to the traditional measures of origin, destination, starting time, ending time, and mode.

Additional requirements exist for long-term forecasting models, including the representation of: changes in demographic and socio-economic characteristics of the region (including household members' employment status and household vehicle holdings) and the interaction between transportation and land use (including households' residential location choice).

Data collected by conventional methods and maintained by MPOs support some of the model development efforts that are called for by these requirements. It is, however, needed that data requirements be identified and data collection methods be refined toward the development of fully activity-based demand forecasting models.

5. STRUCTURAL-EQUATIONS APPROACHES TO ACTIVITY-BASED DEMAND FORECASTING

Structural equations modeling approaches have been used to capture relationships among macroscopic indicators of activity and travel, and to explore how these indicators are associated with variables that are considered to "explain" behavior, e.g., household structure and vehicle ownership. Structural equations approaches facilitate the examination of alternative hypotheses about the "causal" relationships among behavioral indicators, while reducing computational requirements substantially, even when limited-dependent variables are involved, by adopting the method of moments for the estimation of model coefficients (see Bollen, 1989). Examples can be found in RDC, Inc. (1993), Golob and McNally (1995) , Golob *et. al.* (1996), and Kitamura and Fujii (1996).

Golob *et. al.* (1996) presents probably the most elaborate model system in this group of studies. The endogenous variables of the model system are: "work/school activity duration," "work/school journey time," "maintenance activity duration," "maintenance journey time," "discretionary activity duration," and "discretionary journey time." Maintenance activities include "weekly grocery shopping, pick up and drop off passengers, personal business and

[7] See Pas (1988).

be logically supported. Furthermore, by concentrating "average" travel demand, the "typical" weekday approach offers no information on the distribution of travel demand over a year. Consequently the approach is incapable of supporting the prediction of the frequency of air quality standard violations. Much work is needed in this area, in terms of both data collection and model development.

Activity-based models, especially the micro-simulation approach described later, meet many of these requirements imposed on travel demand models by the current planning needs. In addition to these requirements, there are several "desirable" features of activity-based forecasting models. Useful models of travel demand analysis and forecasting have been developed that do not necessarily possess all of these desirable features. Yet, developing logically coherent and robust models of activity and travel that are applicable to a wide range of policy analyses, calls for additional requirements. The following list is prepared with short-term forecasting in mind:

- *Mechanisms of activity engagement*: It is desirable that a model of activity-travel behavior explicitly represent the mechanism of activity engagement, while considering the needs and desires for activities and taking into account the availability of resources (e.g., time and vehicles). In addition, it is critically important for travel demand forecasting that the decision to change activity location be explicitly modeled (e.g., a series of comparison shopping activities may be pursued at several different locations, generating a number of trips).

- *Internal consistency*: The model should faithfully represent spatial and temporal continuity of movement, time-space constraints (e.g., Hägerstrand's prisms), continuity in travel mode and various coupling and institutional constraints (Hägerstrand, 1970).

- *Comprehensive activity itinerary*: All activities, both in-home and out-of-home, should be included within the scope of the model, and the substitution between in-home and out-of-home activities should be considered.

- *Activity scheduling*: Forming an itinerary for a day (or a longer span of time) involves placing the activities to be engaged in a sequence (*sequencing* activities) and planning the starting time for each activity (*timing* activities). Previous studies (e.g., Kitamura, 1984) have revealed tendencies in activity sequencing that more mandatory activities tend to be pursued first. It is also expected that preferences do exist with respect to the timing of activities. Tendencies and preferences about activity sequencing and timing must be represented in a model of activity-travel behavior.

- *Inter-personal linkages*: The household is a unit where tasks are assigned to, resources are allocated to, and activities are engaged jointly by its members. Task assignment, resource allocation and joint activity engagement should be properly represented since travel demand generated by a household is determined by these inter-personal interactions.

4. WHAT ACTIVITY-BASED TRAVEL DEMAND FORECASTING MUST SATISFY

When the reduction of peak-period congestion was the major concern of urban transportation planning, daily travel volume by network link was considered as a sufficient measure for planning exercises. The requirement that transportation planning analysis must incorporate emissions analysis, has drastically changed the prerequisites for travel demand forecasting models. In this section, new requirements for travel demand forecasting models in general are reviewed briefly. Following this, requirements for activity-based models are discussed.

Weiner (1993) lists as emissions modeling requirements the six items shown in Table 1. What is evident from the table is that methodologies are called for by which:

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

It would be clear that the most coherent and robust approach to address the first two issues would be to incorporate the time-of-day dimension into the model framework. This is being achieved in some micro-simulation models systems as reviewed later in this paper.

Although several models of household vehicle type choice and utilization have been developed in the past (see Kitamura, 1992), none has been adopted by MPOs so far. More critically, these vehicle type choice and utilization models forecast the total *annual* VMT for each household vehicle, but do not match vehicles and trips. In other words, these models do not determine how the vehicles in a household fleet are assigned to the trips made by the respective household members. Consequently, the information available from them does not support the emissions analysis with the spatial dimension. The most coherent and robust approach to address this issue would be to explicitly model the process of vehicle allocation to trips. This is an area where little attention has been directed in the past.

Table 1
Emissions Modeling Requirements as
Identified in Weiner (1993)

• VMT by hour of the day by grid square
• Average speeds by hour by grid location
• Vehicle mix by hour of the day by grid square
• Proportion of cold starts by hour of the day
• Seasonal variation in VMT, vehicle mix, etc.
• Annual growth in VMT

There is an increasing recognition that predicting travel demand for a "typical" weekday does not adequately support transportation planning decision making. When traffic congestion is not limited to the traditional peak periods of commute traffic, ignoring weekend days can no longer

There are several factors that have made activity-based models practical tools for travel demand forecasting (Kitamura *et. al.*, 1995a). They are: accumulation of activity-based research results; advances in survey methods (e.g., stated-preference (SP) and time-use survey methodologies) and statistical estimation methods; and advances in computational capabilities and supporting software (database software, GIS, etc.). These factors together have created an environment where models of travel behavior can be developed while adhering to the principles of the activity-based approach. In particular, activity-based micro-simulation of travel behavior has become a practical tool for transportation planning and policy analysis.

The advantages of the activity-based approach are summarized in Kitamura *et. al.* (1995a) as:

- *daily behavior*: treats a daily activity-travel pattern as a whole, thus avoids the shortcomings of the conventional trip-based methods;
- *realism*: incorporates various constraints governing trip making, facilitating realistic prediction and scenario analyses; and
- *induced demand*: by representing activity engagement behavior, the activity-based approach can rigorously address the issue of induced or suppressed demand.

In addition, activity-based micro-simulation of activity engagement and travel offers the following advantages:

- *time of day*: predicts travel behavior along a continuous time axis;
- *TDM evaluation*: is capable of realistically assessing the impact of TDM measures on the entire daily travel demand;
- *flexible* and *versatile*: can be modified for specific study objectives or to address various policy scenarios, e.g., to evaluate effects of day-care facilities at work, extended transit service hours, or new transit service;
- *accuracy control*: using synthetic household samples,[6] can produce results with desired levels of spatial and temporal resolutions; and
- *comprehensive evaluation tool*: activity-based approach simulates the entire daily activities and travel. Therefore the effect of a transportation policy on the entire daily activity, not just commute trips, can be evaluated, leading to better benefit measures.

The activity-based approach implies an expansion of the analytical scope because its subject is not limited to the trip. This naturally leads to increased levels of data requirements and analytical complexities. The advantages offered by the approach, in particular the ability to overcome the limitations of the conventional trip-based methods and to address policy options that are important in current planning contexts, more than outweigh the disadvantages. In fact practical forecasting models are being developed as reported later in this paper.

[6] See Beckman *et. al.* (1995) and Kitamura (1996).

One of the possible consequences of these limitations is an over-prediction of mode shift.[5] The problem is compounded by the fact that the modal split phase of the four-step procedure, where disaggregate choice models are often incorporated, tends to be most sensitive to changes in the network level of service. As a result, the four-step procedure may grossly over-estimate mode shift when in fact travel mode may be the last thing travelers wish to change in response to TDM measures.

Also stems from these three limitations is the problem that the four-step procedure will not be able to capture the full impact of a change in the travel environment. Suppose a drive-alone commuter routinely stops by at a grocery store on the way home from work. Faced with congestion pricing, this commuter may choose to take a bus to work, and go shopping by auto at a grocery store near the home base after returning home by bus. The trip-based four-step procedure is not capable of addressing such repercussions brought about by the commute mode change.

These examples illustrate that the four-step procedure is hardly applicable to the analysis of TDM measures. It is also insensitive to the effects of mounting traffic congestion or travel time savings due to traffic improvement. While some of the problems discussed in this section may be resolved by introducing new model elements or modifying some of the components of the four-step procedure, the problems stemming from the atemporal, trip-based structure are difficult to eliminate. Consequently developing effective tools for TDM analysis is impractical within the framework of the four-step procedure.

3. WHY THE ACTIVITY-BASED APPROACH?

The activity-based approach provides a coherent framework for travel behavior analysis and demand forecasting. While statistical associations, rather than behavioral relationships, drove model development of the components of the four-step procedure, the activity-based approach starts with the recognition that a rigorous understanding of travel demand will follow from an understanding of why and how activities are engaged over a span of time. Another important distinction is the recognition that trips cannot be analyzed one by one independently because the activities engaged over a period of time are linked to each other, and consequently the trips made to pursue these activities are also inter-related.

Because the activity-based analysis attempts to develop model systems based on a rigorous understanding of why people travel, resulting models are applicable to a much wider range of situations than is the trip-based four-step procedure. As the examples presented later in this paper show, the activity-based approach offers a better framework for the analysis of TDM measures. The issue of induced or suppressed trips can also be entertained with the approach. In fact most, if not all, of the problems of the four-step procedure described in the previous section can be resolved by adopting the activity-based approach.

[5] Keith Lawton brought this possibility to the author's attention.

development to transportation systems management (TSM) to TDM. And energy and environment have emerged as new concerns of transportation planning. The trip-based, four-step procedure that was tailored to the planning needs of the 50s and 60s, just does not serve well in the current planning contexts.

The discussion in the rest of this section focuses on three major sources of problems that are most deleterious in the current transportation planning contexts: (i) lack of behavioral basis, (ii) lack of the time dimension, and (iii) trip-based model structure.[4]

Lack of Behavioral Basis: Attempting to represent demand by the serially linked four model components presents problems under certain conditions. Suppose parking pricing is implemented in a downtown area, prompting some travelers to choose suburban destinations. This change in trip attraction, however, would not at all be accounted for by the four-step procedure because trip attraction is determined in the trip generation phase, which is not sensitive to parking cost. Likewise, the impact of new highway segments on trip distribution would be under-estimated, while mode shift could be over-estimated, because of the typical insensitivity of trip generation/attraction models to accessibility. Issues of induced trips and suppressed demand are difficult to address within the structure of the four-step procedure. These problems arise because the four-step procedure does not represent the decision mechanisms underlying travel behavior. As noted earlier, people do not decide how many trips to make before deciding what to do, where to go, and how to get there.

Lack of Time Dimension: The fact that the four-step procedure does not incorporate the time-of-day dimension is curious since congestion — which has been the single most important concern of transportation planning — occurs with the concentration of demand in the same geographical area within the same time period. The absence of the time dimension necessitates the use of purely empirical, often dubious, procedures to determine hourly demand volume. It makes it difficult to thoroughly analyze peak spreading, assess impacts of congestion pricing, or predict the distribution of cold and hot starts.

Trip-Based: The four-step procedure treats each trip as an independent entity for analysis. This assumption, on which the structure of the four-step procedure hinges, leads to a number of serious limitations which stem from the fact that trips made by an individual are linked to each other and the decisions underlying the respective trips are all inter-related. For example, consider a home-based trip chain (a series of linked trips that starts and ends at the home base) that contains two or more stops. The four-step procedure would examine each trip separately and determine the best mode for it, leading to two major problems. Firstly the result may violate the modal continuity condition; mode choice for a trip with non-home origin is conditioned on the mode selected for the first, home-based trip. Secondly, the result ignores the behavioral fact that people plan ahead and choose attributes of each trip (including mode, destinations, and departure time) while considering the entire trip chain, not each individual trip separately.

[4] The discussions in the remainder of this section are drawn from Kitamura *et. al.* (1995a) and partially expanded.

2. A CRITICAL REVIEW OF THE TRIP-BASED, FOUR-STEP MODELS OF TRAVEL DEMAND

In the Detroit Metropolitan Area Traffic Study (DMATS) which started in 1953, Weiner (1992) reports that "Much of the work was done by hand with the aid of tabulating machines for some of the calculations." Given the cost and speed of computation, and the software available for statistical analysis and data-base management, it is not surprising that the travel demand model systems developed in the 50s and 60s involved:

- aggregation of data to make the data-base manageable and to reduce computational requirements;
- simple models that do not require lengthy computation for the estimation of their parameters and preparation of forecasts; and
- parsimonious models that include only the most salient variables.

When tabulating machines are the only computational tools available, inverting a 5-by-5 matrix would not be a trivial task. Consequently linear regression models could include only a limited number of explanatory variables. Likewise, modal split models were zone-based and incorporate only a few, most obvious explanatory variables.

It should nonetheless be acknowledged that the simplifying assumptions adopted in the four-step procedure facilitated quantitative analysis of urban passenger travel demand, using home-interview survey results, land use inventory data, network models, census and other existing data, and computational capabilities that were available decades ago. When reviewing transportation planning models that are currently in use, however, one may notice that some are still bounded by the limitations in computer hardware and software that existed when the four-step procedure was being developed.

The development of the four-step procedure was motivated by the planning needs of the 50s and 60s when the expansion of transportation infrastructure was of primary concern. This is the period of the "suburban boom," whose four main foundations were: new road, zoning of land uses, government-guaranteed mortgages, and a baby boom (Hall, 1988). With the rapid suburbanization, what was needed was road networks that effectively connected the central city as the place of employment and suburbs as the place of residence. Commute trips to and from work were of primary concern when road networks were planned. Given these planning contexts, one would agree that the trip-based, four-step model system is a streamlined procedure which adequately served the planning needs of that time. Indeed it represents skillful simplifications to develop a practical tool to meet the planning challenges of the time.

The procedure, however, contains limitations, some of which were discussed extensively when disaggregate choice models were proposed in the 70s. Furthermore, significant changes took place since the 50s and 60s in demographic and socio-economic characteristics of households (e.g., more working women, small households and single-parents), urban forms (e.g., commercial developments in suburbs), industrial composition, distribution systems (e.g., shopping malls), and consequently in travel patterns. Planning emphases have shifted from infrastructure

This, however, is not to suggest that the activity-based approach is inept in providing useful planning information. In fact, the conceptual framework of the activity-based analysis offers features that facilitate coherent analysis of travel demand. While no widely accepted model of activity engagement has been in existence, "utility-maximizing" discrete choice models of activity engagement and statistical models of activity durations have served as critical components of micro-analytic models of activity-travel behavior. As is reviewed briefly in this paper and is treated more rigorously in Axhausen and Gärling (1992), Gärling *et. al.* (1994) and Kurani and Kitamura (1996), research is progressing at healthy rates in areas that support the construction of activity-based model systems of travel demand forecasting.

The forecasting models reviewed in this paper can be classified into two groups:

- structural equations model systems of measures of mobility and activity participation, and
- micro-simulation model systems of individuals' activity engagement and travel.

The structural equations model systems capture relationships among individual-level, macro-measures of mobility and activity participation (e.g., number of trips, total travel distance, total travel time and time allocated to each type of activity) and exogenous (explanatory) variables (which are typically person and household attributes, network variables, and land use information). In the sense that they do not explicitly model the behavioral mechanisms underlying activity participation and travel behavior, but merely trace salient statistical relationships among indicators of activity-travel behavior and explanatory variables, one may not consider them truly "activity-based." Yet they have proved to be effective tools in addressing a range of issues including that of induced travel demand.

The latter, micro-simulation approach includes modeling efforts that attempt to replicate the decision mechanisms underlying activity engagement and travel. Several model systems have so far been proposed. They each have unique focuses, e.g., memory structure, search processes, activity scheduling, adaptation, and time-space constraints. These models are by definition microscopic and require types of data that have not been used in traditional travel demand analysis (Axhausen, 1995, considers data needs for models of activity scheduling). Yet, prototypes exist that rely on information that is mostly available from local planning organizations.

Reviewed in this paper are samples of studies from these two groups, in which activity-based models have been applied to demand forecasting and policy analysis. The objectives of this review are to summarize the progress so far made in the application of activity-based models to demand forecasting, and to demonstrate the benefits this approach will offer when it is fully developed. In the next two sections, the limitations of the conventional trip-based models and the reasons why activity-based models should be used, are discussed. In Section 4, requirements for activity-based demand forecasting are discussed. Application examples of structural equations models and micro-simulation models of activity and travel are presented in Sections 5 and 6, respectively. Section 7 offers conclusions.

- Focus on sequences or patterns of behavior, not discrete trips;
- Analysis of households as the decision-making units;
- Examination of detailed timing and duration of activities and travel;
- Incorporation of spatial, temporal and inter-personal constraints;
- Recognition of interdependence of among events; and
- Use of household and person classification schemes based on differences in activity needs, commitments and constraints.

Many studies have been undertaken, placing different levels of emphasis on each of these points. Reviews of activity-based studies accumulated thus far can be found in Damm (1983); Jones (1983); Kitamura (1988); Jones *et. al.* (1990); Axhausen (1990); Axhausen and Gärling (1992); Gärling *et. al.* (1994); Jones (1995), and Kurani and Kitamura (1996).

The activity-based analysis is now entering the stage of producing practical tools for policy analysis and demand forecasting. The tools that are being developed may look quite different from the conventional, trip-based tools of travel demand analysis. Trip-based models typically determine the number of trips first, and then determine the attributes of these trips to produce demand forecasts. This, however, is not consistent with the way we behave. No one would think about how many trips to make when developing a plan for a day; rather, one would think about what she wants to or needs to do, where the activities can or need be engaged, and, only then, would think about how to visit these places. Importantly, how many trips will be made depends on how the visits to different places are sequenced and combined into trip chains. Trip-based approaches to travel demand forecasting thus rest on dubious behavioral ground.

Activity-based demand forecasting, then, should be based on a model of activity engagement, and then should forecast the number of trips and their attributes, given a set of activities to be pursued. Modeling activity engagement, however, is not at all a trivial task. Kurani and Kitamura (1996) note that

> "the paradigm [of activity-based analysis] has yet to develop or adopt a comprehensive theory of activity participation. ... Lacking such a theory ..., we are able to assess neither the motivations for choosing to participate in a given activity nor the decisions as to when and for how long to engage in a chosen activity. Chapin (1978) applied a simple theory based on Maslow's "hierarchy of needs" (Maslow, 1970) in his investigation of differences in activity patterns between different socio-economic groups of people. Tonn (1983a, 1983b) delineated a system of activity participation, but acknowledged he had to draw on an eclectic blend of psychological theories and maxims, none of which could be regarded as widely accepted. Bhat and Koppelman (1993) have proposed a framework of activity program generation, but this framework is not a direct link between activities and needs."

Presumably this is where the challenge in activity-based analysis lies. For example, Gärling and Garvill (1993) propose that investigation be made into how the activities performed are related to the individual's goals.

APPLICATIONS OF MODELS OF ACTIVITY BEHAVIOR FOR ACTIVITY BASED DEMAND FORECASTING

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1. INTRODUCTION

In the period of about two decades since the activity-based approach to travel demand analysis was proposed, extensive empirical results have been accumulated, methodologies for collecting data needed for activity-based analysis have been developed, models capturing various aspects of activity-travel behavior have been formulated, and model systems for demand forecasting are now being constructed. The activity-based approach remained largely within the domain of academic research until recently, when the limitations of the conventional, trip-based demand forecasting tools in the current planning contexts were widely recognized.[3] In fact the activity-based approach is the only approach that can offer coherent frameworks for policy analysis and demand forecasting with the wide range of travel demand management (TDM) and other policy measures that are being considered for improved mobility and reduced environmental impact.

Jones *et. al.* (1990) provide a comprehensive definition of activity analysis as: it is a "framework in which travel is analyzed as daily or multi-day patterns of behaviour, related to and derived from differences in life styles and activity participation among the population." The "emerging features" of activity analysis are identified (Jones *et. al.*, 1990) as:

- Treatment of travel as a demand derived from the desires, demand to participate in other, non-travel activities;

[3] Kitamura (1988) attributed this inattention by the practitioners' community to the fact that the activity-based approach is not suited for the evaluation of capital-intensive, large-scale projects, but it is better suited for refined, often small-scale transportation policy measures. Unfortunately small-scale projects can rarely afford elaborate analysis. This is no longer the case, at least in the United States where the importance of refined transportation control measures is well recognized and efforts are being made to promote their implementation and to assess their potential effectiveness.

Lee-Gosselin, M. (1996) Scope and Potential Of Interactive Stated Response Data Collection Methods. *Proceedings of the Conference on Household Travel Surveys: New Concepts and Research Needs*, Irvine California, March 1995. Conf. Proc. 10, TRB 115-133.

Pendyala, R., R. Kitamura and D. Reddy (1995). A Rule-Based Activity-Scheduling Algorithm Integrating Neural Networks of Behavioral Adaptation. Paper presented at the Conference "Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns" Eindhoven, The Netherlands, May 1995

The limitation of data to household cross-sectional will also probably limit model development to utility maximization, and raise issues of temporal truth. However, in my opinion, activity pattern, or travel pattern based models using utility maximization are preferable to trip based models, and would represent a considerable improvement over current practice.

I am also of the opinion that it is time to consider smaller samples of households, with real compensation for the level of effort, together with the use of direct contact surveys utilizing interactive computer based techniques.

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The opinions and conclusions drawn remain the responsibility of the author.

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DATA COLLECTION METHODS

A plea!

The Irvine conference on household surveys brought to the fore issues of non-response and biased samples. Our experience in Portland with a relatively complex activity survey shows a much worse than expected non-response bias (both household and item). There has been a direction in the US that has moved us away from in-home surveys and towards mail-back and telephone. We have put more value on quantity than quality. With a section of the population being functionally illiterate, the use of written diaries does not make sense, as an example, the Portland survey has a good sample of the very literate, as a look at reported occupations discloses. The answer does not lie in simplifying the questions, (we would still have some problems), the illiterate and semi-literate have lives, activities and travel, and make the same kind of behavioral decisions as others – we need to get their input, and in the same detail!

We should seriously evaluate the use of more carefully chosen, smaller samples, using direct contact and paying for cooperation (their time). Data collection needs to be automated (laptops etc.), and we need to design interactive stated response experiments that key directly from revealed data at the same collection time. There are examples of this approach outside the US.

I would also pose a heretical question, is it time to consider surveying a single person from each household? We are looking for complex information on revealed and stated response which increases the household response load. Does the increased household load lose more than is gained in explicit household member interaction? The alternative might be to space the household members over several days, or use multiple interviewers. The ATAQ survey suggests a practical in-between approach where detail was collected on all members, the changes were applied to the major traveler and responses of other members were collected if the responses of the major traveler would affect their pattern. However the main respondent was always an auto driver, so that the collected trip characteristics were relatively simple.

If we move to direct contact surveys, we may also want to depart the flawed world of random digit dialing samples.

CONCLUSIONS/OPINIONS

My conclusions are that both revealed household activity (cross-sectional) and stated response techniques are needed for near term activity model development. In the case a study area with no existing household survey, the fielding of the revealed and stated response should be a joint (and simultaneous) exercise. For regions with an existing (current) household survey, stated response will still be necessary to answer many policy issues, although the scope may be less onerous. This joint approach gives much more information for the development of better utility maximizing models and is essential for the development of microsimulation models.

In the long run, the joint RP/SR will probably be used as the primary source of data for heuristic model development. In this case, the experiment can be widened to determine the non-constrained choice of activity pattern. This was suggested by Axhausen in his presentation at the Eindhoven conference.

A different and more direct approach is suggested by Ettema, Borgers and Timmermans in their description of the development of SMASH. This is a two-stage experiment:

In the first stage, the respondent details, for a list of activities, last occurrence (when), frequency (per month), time to perform (min. max. and average), the likelihood that this activity will be performed on a predetermined target day (next day), the need for performance with others and information on all known possible locations for this activity. The respondent is also asked to enter travel times for available modes between each pair of activity locations identified. This data was collected in a personal interview using an interactive computer procedure (MAGIC).

In the second stage the respondents were asked to build an activity schedule (interactively), for the following day. All of the information about the development of the activity pattern was recorded by the program, which included checks for feasibility, activity overlap, and time used (by the scheduler). This data was then used to build a model of the activity scheduling heuristics. This kind of approach (determining the revealed choice process) would also appear to provide some promise in the future. Again, application and calibration/validation against the aggregate values from a revealed preference activity pattern would be appropriate.

Both the ATAQ and SMASH examples make use of interactive computer interviewing, with great success. Given the current capability of laptops, it is hard to justify using paper diaries and CATI or mail-back -- complex diaries, with the need for good literacy, lead to obvious response bias problems.

Longitudinal panels offer little in terms of short term application, but much in understanding revealed response to changing situations. For "slow" decisions such as location choice, they are a possible source of revealed data. Given that stated response is assumed to be more suspect when applied over long time horizons, this becomes important. As the questions on joint interaction between land use, activity space and transportation become more insistent, and the need to model, or evaluate this interaction is needed, the need for panel data will be real. This is perhaps, the hardest "sell" in terms of a research objective.

Retrospective surveys may be a viable alternative to panels for understanding slow response decisions, and may certainly yield results in a more timely and less expensive manner than panels, research is needed here to determine valid retrospective time horizons, among other issues.

4. RETROSPECTIVE SURVEYS

This is an area that is not much discussed in transportation literature, however, given the new concern for long run effects of transportation infrastructure on land use and auto acquisition, this might be a fruitful alternative to longitudinal panels. The discussion of retrospectives versus panels is somewhat analogous to the RP-SP debate, only here it is revealed behavior versus stated behavior.

Issues here include: the determination of "true" frequency of the occurrence of the choice (analogous to choice based sampling); the survey of respondents who had not made such a choice, but might have considered it, to determine null response; and the determination of an acceptable retrospective time horizon for various actions of interest.

SURVEY ROLES AND INTEGRATION

Where do the various methods fit, what are their roles, how do we develop an integrated and coordinated approach to data in the short and long term?

I believe the essential base element is the household (or person) activity survey. This is needed, under the utility maximizing paradigm, for both model estimation and for calibration. It is also necessary for the calibration of rule-based heuristic satisficing model development. In the immediate short term, this is the only source of data available, and, in fact constrains the choice of activity models in the short term. The most obvious application is in activity pattern models that use utility maximization.

To date, true stated preference models have been largely limited to trip-based analysis. The consideration of stated response to generate rules and constraints for a satisficing approach would also appear to be a possibility. In terms of short term practicality, this would have to be a combined RP/SR on individuals (rather than households), where a base pattern is revealed and a concurrent stated response is used to probe for both response and decision rules. A recent example of this approach is the Washington survey done as a part of the development of AMOS, which was limited to out of home activity patterns that included a work activity. That procedure could certainly be widened to include all activities, and to include non-workers. The model development could be completely heuristic, or hybrid, including utility elements. The model could in fact be calibrated/validated against the aggregate values from an existing household survey.

Perhaps the best example of a joint RP/SR survey that I am aware of, is the Adelaide Activity-Travel Questioner (ATAQ) - (Jones, Bradley and Ampt). This survey successfully demonstrated an activity approach that considered all family members and measured the effects of changes to the journey of one of them. It was also a computer based survey that was well ahead of its time. The thought that this example is ten years old is humbling. This example of the integration of RP and SR, with enhancement, might well form the basis of survey techniques for moving into fully informed activity modeling.

3. LONGITUDINAL PANELS

Longitudinal panels can be the repeated survey of revealed behavior of the same respondents over time, as their situation or environment changes at a fixed time interval (e.g. every 6 months), or a study of revealed behavior before and after some anticipated change in the system.

It is possible that this kind of study is the only way to obtain data for models of "slow" decisions such as household location and auto acquisition/disposition choices. It is certainly true that this is the only source of revealed preference data for such "slow" decisions. This is also a source for modeling the effects of household transitions (births, deaths, marriage, children leaving home, new job). Its value as a source of information on daily travel choices is more problematical as changes in behavior over time occur as the result of many changes in stimuli. Just as cross-sectional revealed preference has limits on use of many variables that are of policy interest, due to correlation and confoundment, and a large part of the model representing unexplained variance (a reason for SP experiments), so do panels, with the addition of changing preferences over time probably exacerbating this problem.

The use of data of this sort for immediate application in activity models is limited to the use of already collected data. The length of time for development and deployment of this source of data is in the order of 5 or more years. A consideration for this conference is the utility of the use of existing panels (e.g., the Puget Sound survey which only has travel related activities), and the possible value of survey enhancement (in terms of geocoding, and the addition of needed transportation level of service, environmental and accessibility variables between and at household and activity locations). This raises issues of transferability (strongly linked to the enhancement grain — network, geocoding).

From the point of view of the advancement of activity-based forecasting, it would appear that the institution of a longitudinal panel of activity participation, travel and time use would be useful. A discussion issue here is the role of such a survey — to look at "slow" decisions only, to look at stability in activity participation and duration (which could form a strong modeling base if there is temporal stability, and of course lead to model transferability) or to use it as a base for full information on travel decisions?

Another issue is the cost and continuing effort for these types of surveys. It is unlikely that most MPOs can find the political support for a large expenditure on something that has a delayed pay-off (beyond the political term limits of some states).

The final disadvantage is that the design and fielding of many such panels would stretch the skilled resources necessary to design and carry them out. Is it time to look at a national effort – and if so, would this be better as a few projects in well chosen cities, or would it be better to do a nationwide survey in the same way as the National Personal Travel Survey (NPTS)? Should it in fact be integrated with, or replace the NPTS?

Is it worth doing at all?

The real promised strength of stated response is in the formulation of heuristic, rule-based models of adaptation. This has applicability to the policy analysis of control strategies, but to a large extent is still firmly rooted in academic research. Introduction of these techniques into a model paradigm that considers the interaction and feedback between demand and supply has not yet been demonstrated.

The other probable major role for stated response is in the generation of a daily (or weekly) activity-travel "plan" or "agenda" – the desired set of activities contemplated by the person or household. This base pattern is usually assumed to be developed from the revealed preference household activity survey (factored), which in fact displays already constrained choices, or to be generated synthetically. In most of the adaptive models this base pattern is heuristically modified until an acceptable and practical activity pattern is found, following the introduction of some change. In the case of the proposed TRANSIMS formulation this is then modified further following the feedback of the aggregate effects of all decision makers on the system.

For policy analysis in terms of response to TDM actions, this technique is relatively quick to deploy and to develop a model response to actions affecting a specific market segment. The most recent application of this type in the US has been in the development of TDM response on the part of commuters to various policy changes in the Washington DC metropolitan area. This was described as a stated preference survey and was fielded using Computer Aided Telephone Interview (CATI) methods — which meant the sequential rather than parallel (simultaneous) consideration of choices. The results of this survey were used to calibrate the initial element of AMOS, demand response to TDM actions, using neural networks of behavioral adaptation (Pendyala, Kitamura and Reddy). In terms of the Lee-Gosselin taxonomy, this survey could perhaps be described as Stated Adaptation, or on the border between SP and SA. The other example, which will be discussed later, is the Adelaide Travel-Activity Questioner (ATAQ) — (Jones, Bradley and Ampt), which was an early example of joint RP/SR, considering stated adaptation with the activities of all members of the household.

My own view is that this area (stated response) is likely to give us the most effective way of getting information for new activity-based models in a reasonable time period. However, because of complexity, it will mean a move away from the quantitative SP to more qualitative flavors of stated response. The issue here is that transport modelers are (in the main) uncomfortable with stated preference as compared with revealed preference. It will be important, in the workshop, to explore the value of the more general stated response techniques and, indeed, the value of the discovery of rule parameters in constraining outcomes. While we are uncomfortable with non-statistical models and measures, there is no reason to believe that because we cannot look at the goodness of fit statistics, non-statistical methods are inherently inferior to statistical methods. How well, or realistically the model can be specified, is probably as important as having a model which has good goodness of fit measures using variables whose coefficients leave much of the behavior unexplained.

Taxonomy of stated response surveys: Martin Lee-Gosselin

BEHAVIORAL OUTCOMES	***CONSTRAINTS*** (expressed as attributes, personal,/household/social/spatial/supply, etc.)	
	Mostly Given	***Mostly Elicited***
Mostly Given	**STATED PREFERENCE** **(focus = tradeoffs, utility)** *"Given the level of attributes in these alternatives, which would you prefer:* *[A]....? [B]....? [C]....? etc..."*	**STATED TOLERANCE** **(focus = limits of acceptability and thresholds for change)** *"Under what circumstances could you imagine yourself doing:* *[r1]....? [r2]....? [r3]....? etc..."*
Mostly Elicited	**STATED ADAPTATION** **(focus = reactive and trial behavior; problem-solving, rules)** *"What would you do differently if you were faced with the following specific constraints: [...detailed scenario]"*	**STATED PROSPECT** **(focus = learning processes; information seeking; the imaging, formation and testing of choice sets; metadecisions)** *"Under what circumstances would you be likely to change your travel behavior and how would you go about it [...broad context]"*

For use in utility maximizing activity models, the formal stated preference approach, with an orthogonal trade-off design has the advantage of quantitative integration with revealed preference. The disadvantage is the difficulty of dealing with complexity of response choices. For example, even without consideration of interaction among household members, a design that in response to (say) congestion pricing can both include the response in the trip (change mode, change destination, change time of day, not take trip) and the alternatives in activity chaining and activity patterns and duration of activities, yields a set of combinations that is impractical.

INTRINSIC STRENGTH

Many regions have recent data from such surveys, with varying levels of in-home activity coverage. These surveys are usually large enough to reveal a large number of different activity patterns, which can be used as a basis for at least an out of home activity pattern based model. Surveys of this type take a minimum of a year to design and field, with another 6 months to get clean the data and append the level of service and accessibility data necessary for model estimation. (This would be an optimistic/aggressive scenario). They can be designed, fielded and used to prepare models within a 2-year time frame. This would have to be the primary source for models that can be implemented now.

2. STATED RESPONSE

This is a collection of methods that can be deployed in a relatively short time frame, and a very promising source of data for the development of activity based models which take into account adaptation, (heuristic) rule based decisions and satisficing. There is a confusion of terms and vocabulary. It is useful to consider the taxonomy suggested by Martin Lee-Gosselin, shown in the following table.

amounts of unspecified time, some of which (like eating) could be done inside or outside the home. The Research Triangle survey dealt with this by only requiring detailing of time used in-home for things that could be optionally done away from home, the rest being lumped into an other category.

Travel As An Activity

The activity surveys preceding the Dallas-Fort Worth survey treated travel as a means, not as an activity in itself. The format was to ask the following information: the first activity of the day, then ask if it included travel, if so, details on the trip were collected; then.... "what did you do next", and ask if travel were needed ... etc. It was noticed during the Portland survey that respondents had difficulty with the concept of travel <u>not</u> being an activity. When the North Central Texas Council of Government's (Dallas-Ft. Worth) household survey was extensively pretested, the same problem was noticed and the questionnaire re-cast with travel as an activity. This instrument is currently in the field.

INTRINSIC LIMITATIONS

The primary limitation of a cross-sectional survey is the assumption that cross-sectional differences in response in many individuals to different situations can be extrapolated into a longitudinal response of specific individuals to a changed situation, which raises questions for TDM policy analysis. If this is not true, questions about temporal stability are raised.

The second limitation is the lack of variation in some specific key variables. The primary variable here is the cost of driving and transit fare. Out of pocket costs of driving are primarily fuel based — constant, the major differences being in fuel economy of the car chosen — rarely included in data for model estimation, and more difficult to include in model application (how do we know which car would have been used by non-car choosers?). In reality the type of car acquired and the number of cars acquired are (or should be) endogenous not exogenous variables, and are a function of fuel price, among other things. For many MPOs the only other car-based cost is parking, in a limited number of activity locations. Transit fares in most US cities are fairly flat, being zone based with discounts for passes. Only a few cities (such as the San Francisco area) have the multiplicity of transit suppliers and the number of tolled bridges that will provide rich enough data on user costs in terms of money.

Research carried out on the Dutch panel data, and the Portland data (discussions with Kitamura and Golob) suggests that travel time increases for the commute are traded off against truly discretionary time: recreation, either in-home or out and household maintenance (chores). The scheme used for Portland is an example of an attempt to create a scheme that allows more insight into trade-off behavior by using a richer set of activity classification than traditional travel surveys. At some point this approach would lend itself to evaluation of the change in quality of life as a way of considering transportation issues. Portland Scheme:

The Portland activity data was collected open-ended and coded to the following set by the interviewer.

Household Sustaining
Meals
Work
Work-Related
Shopping (General)
Shopping (Major)
Personal services
Medical care
Professional services
Household or personal business
Household maintenance
Household obligations
Pick-Up-/Drop-Off passengers

Social Activities
Visiting
Casual entertaining
Formal Entertaining

Personal Enrichment
School
Culture
Religion/Civil Services
Civic

Recreation and Other Diversions
Amusements (at home)
Amusements (Out of home)
Hobbies
Exercise/Athletics
Rest and Relaxation
Spectator Athletic Events
Out of area travel

Other
Incidental travel
Tag along travel

In-Home Activities

There has been considerable discussion on this issue in the development of recent household surveys in the US, with no closure. The practice ranges from no in-home activity classification (obtained in a traditional travel survey) to an attempt to get all in-home activities (e.g., Dutch Panel — all, and Portland — for activities whose duration was greater than 30 min.).

The acceptance of the concept of the modeling of activity sequencing and duration, together with the choice of location and travel (if out of home) requires an accounting for time from waking up to sleeping at the end of the day. The level of detail of in-home activity classification is an important item for discussion. However the approach used in Portland, attempting to get great detail, led to problems with completing the survey until a threshold of greater than 30 min. time use was introduced. Using the 30 min. threshold led to non-reporting of meals, and large

1. *There is in fact a relatively small marginal increase in size and complexity for a full activity survey when compared with the data required in a traditional survey of travel behavior.* As an example, the Portland survey had a mean of a little over 15 activities per household per day, about half of which required travel (15+ activities, 9.2 at home, 5.8 away, with 8+ trips). The activity and time-use survey requires no more household data and no more person data than the travel survey (in Portland 200 items for an average household). The data collected for a trip consisted of an average 32 items, including address elements, or 256 per household per day average. The data collected on an activity with no travel consisted of 8 items or 74 per household per day and the data for an away activity (also 8 items) 47. This gives an average of 577 data items versus 503 items. The increased data collection to include activities thus added 15% in items recorded. (But does not add to the post treatment of address geocoding and the addition of modal impedances). An incidental benefit of this approach is that the focus on activities probably leads to better reporting of short auto trips and non-motorized trips (appears to be true in Portland).

2. *The data collected with the intention of building activity pattern models or activity sequencing and duration can also be used for the estimation of trip chaining (or tour based) models, or of traditional trip-based models.* There is no risk in the fall-back to a less ambitious model, the flexibility to do more has been built in at a marginal cost.

Given that medium-scale (2,000 to 15,000 households) household behavior surveys are typically undertaken only every 10 years or so, it is important to develop the survey in such a way as to maintain maximum flexibility in model development. It is important to consider a possible change in model paradigm.

From the point of view of building either simultaneous, utility optimizing models or sequential decision microsimulation models, the needs for data from the household activity survey appear to be nearly identical in terms of content (but probably not in the detail of that content). The same survey can be used!

DEMANDS ON INSTRUMENT

There are some extra demands on the design of the instrument to include possible activity model use. These include the classification of activities, the determination of the best practical way to obtain in-home activities and whether to include travel as a discrete activity.

Activity Classification

Ongoing surveys and analysis of time use by individuals outside of the transportation community exist (for example the work of John Robinson at the University of Maryland). To the best of my knowledge, none of this work has been done on the basis of all members of the household. However the existence of this source of secondary data suggests that an activity classification scheme that translates to a superset of the secondary data would be useful.

1. A traditional cross sectional survey of household behavior, with minor embellishments to shed more light on the activities from which travel demand is derived.

2. A stated response survey, which investigates individual response to hypothetical variations in the behavioral environment. Stated preference is a subset of this group, using a trade-off exercise in a rigorous experimental design, in order to quantify the responses. Stated response has usually been applied to a limited market segment. Stated response can also be used to explore the existence and parameters of decision rules, which can be used to develop a set of activity plans or agendas which would represent the desired demand set, absent constraints. This might be the way to develop the synthetic activity-travel pattern for the planning region that can be used for the base in the application of adaptation models.

3. A longitudinal panel survey of activities and travel. In the short term, the transfer of adaptation/response to changes in the behavioral environment from an existing longitudinal panel survey is an important consideration. This data source may be the only one that is useful for the development of slow-response behavior such as household location decisions and automobile holdings transactions. Although retrospective surveys to determine decision rules may be quicker and more fertile.

4. A retrospective survey to investigate "slow" response behavior. I am not aware of the use of such a method in the transportation field. However, a household location decision is, in fact a joint consideration of location, auto acquisition and expected travel modes. Auto acquisition/disposition decisions are joint mode choice decisions.

What follows is a closer look at the four sources of data, with the most detail on the methods that are available for immediate application.

1. CROSS-SECTIONAL SURVEY OF HOUSEHOLD ACTIVITIES AND TIME USE

This survey is very similar to the traditional cross-sectional household travel survey, and in fact, the traditional travel survey has out-of-home time use. The classification of activities has been a very simple one, based on an expanded set of "trip purposes" - usually work, school, personal business, medical/dental, serve passenger, social/recreational, convenience shopping, comparison shopping, and eat meal, with the addition of "home" as an origin or destination of a trip.

There has been a gradual progression in the USA of expansion in the scope of the travel survey and a gradual transformation into a household activity survey. This started with the Boston and Los Angeles surveys (1990-1991). Some recent (1994 to 1996) examples of surveys that have been expanded to include in-home activities (to some degree) are Portland, the Research Triangle (Raleigh-Durham-Chapel Hill), Honolulu, Dallas-Fort Worth, and Bay Bridge Corridor (MTC, San Francisco region). Of these, only Portland and the Bay Bridge surveys attempted a set of activities undifferentiated between in-home and out (with moderate success in the Portland case). There are two important points to be made:

Issues include activities to be served, the arrangement of those activities into a daily and weekly pattern, the linking of out-of-home activity patterns into complex tours or journeys, and the consideration of the trade off between in-home and out-of-home locations for an activity. There is also the issue of interaction among household members. While this policy-sensitivity to management and control issues is well known and understood, an emerging concern is becoming important at the MPO level in the Pacific Northwest. That issue is growth, the management of growth, and the effect of the provision (or non-provision) of transport infrastructure and the effect of transport control strategies on growth and livability.

MODEL STRUCTURE

There appear to be two basic approaches to activity based modeling. While a superficial examination of these approaches would suggest the same basic data needs, a closer look reveals some important differences.

The more traditional approach considers a classification into patterns of activity and/or travel. This approach has used utility maximizing and nested logit more recently (for example, the Stockholm model — Algers, Daly, Kjellman and Widlert; and Ben-Akiva and Bowman). This approach has a long history, with STARCHILD (Recker *et. al.*) qtd. in Pendyala Kitamura and Reddy, - one of the first activity pattern based models; the journey or trip chain approach dates back to 1979 (Adler and Ben-Akiva).

A newer and more radical approach utilizes micro-simulation, and rule based and satisficing heuristics in models that seek to simulate the response or adaptation to change (in, for example, the urban infrastructure, transportation infrastructure, transportation pricing, congestion, family transitions). Examples of this latter approach include SCHEDULER (Garling *et. al.*) qtd. in Pendyala Kitamura and Reddy, SMASH (Ettema, Borgers and Timmermans) and AMOS (Pendyala, Kitamura and Reddy). This line of research seems to date from the mid 1980s. The microsimulation approach is consistent with the described (but not detailed) approach proposed in TRANSIMS (Los Alamos).

In practice, both approaches require a cross sectional base of daily activities and travel in order to implement a regional model of travel that reflects the aggregate effect of the disaggregate choices on the supply, and the effect of the ensuing changes in the supply side characteristics on the disaggregate choices (demand). While the utility maximizing approach also needs the revealed preference (cross-sectional) survey for model estimation, it is not clear that this is true for the micro-simulation/-heuristics/-satisficing approach.

DATA SOURCES

There are basically four possible sources of data/information with which to develop activity-based models:

15 1995 at the Beckman Center, Irvine, California. The proceedings have just been released by TRB (PROCEEDINGS 10).

MPO PERSPECTIVE

MPOs are, of course, far from homogenous and many will need to be more strongly convinced that trip based models are inappropriate for such things as TDM evaluation and mode choice analyses. There are two concerns that need to be addressed before even the more progressive MPOs will easily start activity model development and implementation.

The first concern is the perception that the academic community is leading the charge to move to a new paradigm (not necessarily true). There is a lack of a unified vision on the part of the academic community as to what is a reasonable way to proceed. This lack of a clearly articulated direction, and the competition among researchers, leaves the MPO practitioners confused and uneasy. Given the state of the art and the role of academics, to raise questions and suggest answers, this lack of a unified direction is perfectly reasonable.

I would suggest that the real problem is that the practitioners (public and consultant), are more concerned with maintaining the safety and security of current practice, than they are with the clear limitations of current practice. I think also, that most of us are so busy that there is little allocation of time to acquire an awareness of research that shows promise, and examples (overseas) of applications of this research. Perhaps we would achieve more if we see it as our (practitioners) job to develop a somewhat unified approach in the development of applications. Unless we do, trip based models will be with us for many more years.

The second concern comes from the fact that MPOs (and their consultants) are almost always in a production mode — modeling regional plan alternatives, conducting Major Investment Studies, trying to model TDM actions, doing air quality conformity evaluation. The flow of federal funds to a metropolitan region depends on this pipeline, and the flow of funds is the reason for being ....! It follows that a strategy of gradual replacement of the trip-based process — replacing elements of current models, and using adaptive models initially as an adaptation of the forecasts of the emerging regional models might be important. An effort to get some agreement on where we want to go and a clear plan for gradual implementation, a picture of the trajectory from the existing models to the new, would seem to be a worthy goal.

MODEL STRUCTURE AND NEEDS

It is axiomatic that the needs of the proposed model(s) drive the definition of data needed to support their development. This conference is about model structure development, with data needs becoming clearer from the recommendations that are made.

From the point of view of developing and choosing surveys, it is important to first visualize where models are headed. The needs today are for policy-sensitive models that can address transportation demand management actions in the context of how individual decisions are made.

ACTIVITY AND TIME USE DATA FOR ACTIVITY-BASED FORECASTING

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ABSTRACT

This paper, written from a practitioner perspective, briefly discusses model structure direction and implied needs. The models are categorized into two basic groups, activity pattern utility maximizing and micro-simulation approaches utilizing rule-based and satisficing heuristics. The four major possible sources of information for activity models: cross-sectional household (revealed preference), stated response, longitudinal panels and retrospective surveys are discussed, with the level of detail being higher for methods with short term applicability. The surveys are also discussed in the context of the two basic model categories. The conclusion is that both cross sectional and stated response are needed in the short term, that the use of cross sectional data alone may limit model development to utility maximizing models, and that the combined use of revealed and stated response is necessary for the development of micro-simulation models. Data collection methods are briefly discussed and consideration of direct contact interactive computer based surveys is suggested.

INTRODUCTION

I am a modeling practitioner at a Metropolitan Planning Organization (MPO). For the past several years we have been engaged in the development and deployment of surveys that will allow the introduction of either journey based (as distinct from trip based), or activity based models. My intention here is to examine the various approaches and data sources, and attempt to persuade, based on my experience and (slowly growing) awareness.

The stated purpose of this conference is to identify activity based techniques that can be used *now* by MPOs and state DOTs, and to recommend actions for advancing the state of the art of activity-based travel demand forecasting. The purpose of this resource paper is to demystify data needs for near-term application, and to suggest data needed for advances in the state of the art in activity based forecasting. The intention is to raise issues for discussion during this conference.

There is no intention of duplicating the detailed coverage of household travel surveys in the *Conference on Household Travel Surveys: New Concepts and Research Needs* held March 12-

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4 The term "failure" was originally used in this literature because of the applications in medical science and industrial engineering, since the former dealt with the duration of a patient's survival after surgery or treatment, while the latter dealt with the length of time before a part failed.

5 Specifically, Bhat (1996a) incorporates a non-parametric baseline function as well as non-parametric control for heterogeneity.

6 While air quality has been the focus recently in the U.S.A., in other industrialized countries there is considerable interest in the concept of "sustainability". It is interesting to note that both of these concerns lead to a need for better models and analysis tools — tools that can deal with demand management strategies and that are more accurate and precise.

7 In part to protect against criticisms of their work, it has become standard for MPO's and other agencies developing travel demand models or undertaking household travel surveys, to constitute a group of "experts", generally referred to as a Peer Review Group or Peer Review Panel, to advise the agency and/or the consultant undertaking the model development work.

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are not modeled in traditional approaches to travel demand analysis, yet they require our attention if our models are to be suitable for addressing contemporary planning and policy analysis issues.

Computational process models, in particular, open up completely new possibilities in travel demand modeling. However, these models are quite different from the conventional mathematical-statistical approaches commonly used in travel demand modeling, thus it may take some time and comparative analyses before this approach becomes accepted in the travel forecasting community. Specifically, there is a need to develop methods for calibration and validation of such models.

The diverse methodologies being employed at the current time to model activity-travel behavior, and the variety of phenomena being modeled, is both good news and bad news. The good news is that the activity-based approach is seeing a considerable resurgence of interest, specifically in moving from analysis, description and understanding to modeling and prediction, with a variety of methodologies being applied to model a wide set of phenomena. The bad news, from the point of view of practitioners, is precisely the diversity that makes the field such an exciting and vibrant area of research currently, since the practitioner is faced with the problem of which methodology to select. It might well be some time before the field sees a period of consolidation with one or two methods emerging as standard approaches for application in policy analysis and planning.

At the same time, we should recognize that different tools are needed for different jobs. Thus, while a structural equation model of the type described in Section 3.1.3 does not provide us with link flows, nor an origin-destination matrix, it does allow us to examine some of the implications of changes in sociodemographic characteristics and/or general changes in the transportation system (such as increasing congestion levels throughout the system), without the need to resort to detailed network analysis, while taking into account some important dependencies that are not well accounted for in other modeling approaches. For some planning and policy studies, this level of detail would be quite sufficient. In other cases, of course, this type of model would be quite inadequate.

ENDNOTES

1. Some characterize the difference between economists and sociologists as follows: economists study the choices that people make, while sociologists study why people have no choices.
2. It should be noted that with the development of more flexible and powerful discrete choice models, such as the nested logit model, researchers are now beginning to apply these models to an interrelated set of choices. For more details, see Section 3.1.4 of the this paper.
3. The AMOS model is described in detail by Kitamura in another paper in this volume, so the interested reader can consult that paper for more detail than is provided here. Kitamura's paper also describes another prototype CPM, called PCATS, which is based on the notion of time-space prisms developed by Hagerstrand (1970). Again, the reader interested in more details can consult Kitamura's paper in this volume.

asked to differentiate only those in-home activities that could have been substituted for by out-of-home activities (such as eating, exercising, amusements, etc), while all in-home activities that could only be done at home were designated as "in-home".

The Portland portion of the data from the Oregon-Southwest Washington survey has already stimulated or facilitated a considerable amount of research — see earlier descriptions of work by Golob (1996), Golob & McNally (1995), Lu (1996), Vaughn *et. al.* (1997) and Speckman *et. al.* (1997), while Principio (1996) used the Raleigh-Durham data in her recently completed study of lifestyle and travel behavior. Further, Lawton and his staff at METRO Portland, with the assistance of Cambridge Systematics, Inc., are engaging in the development of a new set of travel demand models that incorporate trip chaining and daily activity schedules, based on the earlier work of Ben-Akiva and Bowman (1995).

The availability of datasets containing both travel and activity information will very likely stimulate and facilitate continuing research and development of activity-based travel models in the immediate future.

5. DISCUSSION & CONCLUSIONS

This paper examines recent and on-going advances in activity-based travel demand modeling. The discussion of the advances in activity-based travel modeling is organized in terms of the methodologies being employed and the phenomena being modeled, and is set in the context of the long and rich tradition of activity-based travel demand analysis.

The paper finds that advances in activity-based travel demand modeling have been made recently at a rapid pace, and that this pace is likely to be sustained by current research and development activities. The paper argues that the recent and current advances are due to a combination of factors, including (1) technical advances in computer hardware and software, statistics, and behavioral sciences, (2) institutional factors that highlight the need for improved travel demand models, and (3) data availability reasons. In addition, the fact that the activity-based approach has been under development for the past 20 years means that this is a very opportune time to be moving the field from a focus on description, analysis and understanding, to an emphasis on modeling and forecasting. In any case, contemporary planning and policy analysis questions cannot adequately be addressed by existing travel demand forecasting tools.

The overview of recent and current work in activity-based travel modeling provided in this paper shows that a wide variety of methodologies are being advanced and employed in modeling a variety of aspects of activity-travel behavior. Some of the methodologies that are being applied are either new or relatively new to the travel demand modeling field, including computational process models, structural equation models, and hazard-based duration models, while discrete choice models (primarily multinomial logit and nested logit models) have previously seen extensive use in travel demand modeling. At the same time, a wide variety of aspects of travel behavior are being modeled, including participation in in-home and out-of-home activities, dependencies among household members, and daily activity-travel patterns. These phenomena embarked on a program of research. This program, known as the Travel Model Improvement Program, addresses the linkage of transportation to air quality, energy, economic growth, land use and the overall quality of life. The program addresses both analytical tools and the integration of these tools into the planning process to better support decision makers. This program has provided a major impetus for the development of new travel forecasting tools and the improvement of existing tools.

Another institutional factor that has had a major role in the current push for the development of new approaches to travel demand forecasting is the law suite brought against the Metropolitan Transportation Commission (MTC) in the San Francisco Bay Area by the Legal Defence Fund of the Sierra Club and Californians for a Better Environment. This suit, which tied up MTC's model development staff for almost 2 years, put planning agencies on notice that their travel forecasting models could be the subject of very careful scrutiny by environmental groups and others with particular interests.[7]

4.3 Data Availability

A third important reason for the recent and continued progress in activity-based travel modeling is the availability of data sets that are well-suited to the development of such models. Specifically, in the United States, MPO's have been moving in recent years away from traditional travel surveys, in which respondents are asked "where did you go?", toward surveys in which respondents are asked "what did you do ?". These latter surveys collect information about activities and the travel undertaken to reach those activities. That is, travel is set in the context of the daily activities undertaken by the respondent. For this reason, such surveys yield higher trip rates, especially for short, infrequent trips by non-motorized modes of travel.

The first metropolitan-wide household travel survey in the USA to collect activity information appears to be that conducted in Boston in 1990 (Stopher, 1992), followed by the survey conducted in Southern California in 1991. Both of these surveys collected information only on out-of-home activities, and the related travel, and the survey format was very similar to a traditional household travel survey, except that the question "where did you go?" was replaced by the question "what did you do?". Some recent household travel surveys, however, have considerably extended the scope of such surveys by collecting information on activity participation (or time use) both in and out-of-the-home, as well as any travel undertaken to reach activities. In particular, surveys undertaken recently in Oregon-Southwest Washington, Raleigh-Durham and San Francisco, all attempted to collect information on all out-of-home activities and the related travel, as well as selected in-home activities, for a 48-hour period (the 48-hour period was chosen in order to capture some of the day-to-day variability that earlier activity-based research showed makes up a significant fraction of the total variability in many aspects of travel behavior).

In the Oregon-Southwest Washington and San Francisco surveys respondents were asked to report in-home activities only if they were 30 minutes or longer in duration. However, in the Raleigh-Durham survey respondents were asked to report all in-home activities, but they were

There are three primary reasons for the recent and on-going progress in activity-based travel modeling; namely, technical reasons, institutional reasons and data availability reasons. Each of these reasons is discussed in the sections below.

4.1 Technical Factors

From the technical point of view, the major reason for the recent advances in activity-based travel modeling is the continued rapid development of computer technology, both hardware and software. Such developments allow researchers to store and process large data sets relatively easily, estimate models that previously could not be estimated because of the required computational resources. In particular, enhanced computational capabilities, coupled with the availability and use of Geographic Information Systems (GIS) to code, store and manipulate geo-referenced data bases is encouraging researchers to develop models that deal with point-to-point movements, rather than zone-to-zone movements (see, for example, Speckman *et. al.*, 1997). Other technical reasons for the recent progress in activity-based travel modeling are advances in the behavioral sciences and in statistical methodologies.

4.2 Institutional Factors

Some years ago the present author wrote a paper addressing the question "Is travel demand analysis and modeling in the doldrums?" (Pas, 1990). The conclusion reached in that paper was that, from a scientific viewpoint, travel demand analysis and modeling was certainly not in the doldrums and that much interesting research was taking place. On the other hand, that paper concluded, travel demand analysis and modeling was very much in the doldrums from an institutional standpoint, since there was little institutional interest in the development of new travel demand modeling techniques and hence very little funding for research and development. (At the same time, funding sources were known to be expressing concerns about the relatively slow rate of progress in the development of activity-based travel forecasting techniques that could be used in planning and policy analysis. This situation, of course, was a classic "catch-22").

If one were to examine the state of travel demand modeling today, from an institutional point of view, one would have to conclude that travel demand analysis and modeling has experienced the "winds of change". In the U.S.A., the Clean Air Act Amendments (CAAA) of 1990 and the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 provided the impetus for the development of new techniques, through the emphasis these pieces of legislation placed on policies whose impacts could not be adequately addressed with conventional travel demand modeling techniques.[6]

In response to the pressures to develop new and more flexible travel demand models, created by the Clean Air Act Amendments of 1990 and the Intermodal Surface Transportation Efficiency Act of 1991, the U.S. Department of Transportation and the Federal Highway Administration, in cooperation with the Environmental Protection Agency and the U.S. Department of Energy, interdependencies and linkages that exist within households. This approach assumes that each activity-travel pattern has a "skeletal" structure that can be defined by estimable elements. Once the skeletal structure is specified, it imposes time-space constraints and simplifies the simulation of the remaining details of the activity-travel pattern. The daily activity-travel pattern is to be generated by a two-stage procedure in which the skeletal pattern will be generated based on sociodemographics and then the pattern details will be simulated based on observed probability distributions.

3.2.4 Summary

As with the methodologies section above, this section shows that there is a wealth of recent and on-going activity-based travel demand modeling research, and that this work encompasses a wide range of methodologies as well as phenomena. While much of this work deals only with parts of the overall problem (not the daily or weekly activity-travel behavior of households and their members), the foundations are rapidly being put in place for the development of a comprehensive, integrated modeling framework.

4. WHY ARE WE MAKING PROGRESS NOW IN ACTIVITY-BASED TRAVEL MODELING?

As noted earlier, the activity-based approach to travel demand analysis and modeling has been under development for the past 20 years, so it is reasonable to ask why this approach has seen relatively little application to transportation planning practice in the past, and why there is considerable interest and effort now in developing and applying activity-based travel forecasting models. The first part of this question has been addressed by others in the past. In particular, Kitamura (1988) undertook a careful review and assessment of activity-based travel modeling, with a specific interest in understanding the limited practical applications of the approach up to that time. He came to the conclusion that while the activity-based approach to travel modeling could contribute to many areas of transportation planning, there were a number of reasons why the approach had not been applied more widely to addressing policy and planning problems. The reasons cited by Kitamura include a resistance to change among practitioners and the lack of effort by activity analysts to provide the practitioners with readily usable methods, as well as the perception that activity-based methods are predominantly useful for analyzing the impacts of non-capital intensive options, which can often be examined without systematic analysis tools.

However, the times have changed, and considerable progress is now being made in the activity-based approach to travel demand. Specifically, the development of travel forecasting models founded in the concepts of activity-based travel analysis has gained much momentum in the past few years. Some of these models are being applied on a prototypical basis in some regions and we expect that such models will start to be used in transportation planning practice at the leading MPO's within the next few years.

Townsend (1987) developed a framework for the development of such models. However, modeling these dependencies is particularly difficult, and only recently have researchers begun tackling this task.

Golob and McNally (1995) recently used the methodology of structural equation models (see Section 3.1.3) to develop a joint model of out-of-home activity participation and the resultant travel of male and female couples (married or unmarried) who are heads of households. The research aimed at identifying the interactions between activity participation and travel and between the two individuals being modeled. This research, using the data collected in the Portland area during the recent Oregon-Southwest Washington Household Activity Diary Survey (see Section 4.3 below), demonstrates the existence of, and provides quantitative estimates of the effects of out-of-home activity participation on travel behavior and the interdependencies between the male and female household heads in their activity participation and travel.

In addition to the work of Golob and McNally (1995) discussed above, we note here the on-going work of Lawson (1996) , which (as mentioned above) aims at capturing interpersonal dependencies in the context of in-home versus out-home activity trade-offs. The reader should also note that Wen (1996) aims at incorporating interpersonal interdependencies into his stop and tour generation model (see Section 3.2.3 below).

3.2.3 Daily Activity-Travel Patterns

There are a number of efforts currently underway to model daily activity-travel behavior, in addition to the work of Ben-Akiva and Bowman (1995) that was described in Section 3.1.4 above. For example, Wen's (1996) dissertation research aims at developing an operational econometric model system for generating complex daily activity-travel patterns. Specifically, his model deals with stop and tour generation and the assignment of stops to tours, as well as the location for each stop and the mode for each tour, in an integrated model system. This research also attempts to incorporate interpersonal dependencies in the model system.

One of the concepts that is integral to the AMOS model (see Section 3.2.1 above) is that of using microsimulation techniques to predict a traveler's adaptation from the baseline (or current) activity-travel pattern. There are two directions being followed currently to develop these baseline daily activity-travel patterns for all the households in a metropolitan area, given the data from a household activity-travel survey and the sociodemographics of all the households in the area (the latter can be generated from census data using a technique such as that of Beckman *et. al.*, 1997). Kitamura (1995) is developing a technique in which the characteristics of the set of activities is generated sequentially using a Markovian approach. The individual's daily activity-travel pattern is formulated as a triple of vectors comprising the set of activities engaged by type, the set of durations for the activities, and the set of locations of the activities engaged.

Vaughn *et. al.* (1997) are approaching the same problem as Kitamura with the goal of generating the daily activity-travel patterns of households and their members in such a way as to replicate the distribution of activity travel patterns at the census block group level and recognizing the home and out-of-home time allocated to discretionary activities. The model is formulated as a doubly-censored Tobit model, while requiring only the assumption that one of the activities is engaged in on the day in question (i.e., the person engages in some discretionary activity, either at home, out-of-home, or both.) The explanatory variables in the model are work schedules, commute characteristics, as well as residential, household and personal attributes. A weekly time use data set from the Netherlands is used in the empirical analysis, and the data are treated as repeated daily measurements. An error component is introduced into the model to deal with the heterogeneity in the data set comprising repeated measures of daily time use for each of the respondents. The model is estimated using a non-parametric approach, employing mass points.

The estimation results show that individuals who work on a given day tend not to engage in discretionary out-of-home activities. However, those who work more hours per week do tend to spend a larger fraction of their discretionary time out-of-home. Individuals who spend more time commuting spend more time on in-home discretionary activities. Gender does not, by itself, seem to affect in-home/out-of-home time allocation, but child rearing does. Larger households tend to be more in-home oriented, while income and number of vehicles and flexible work hours are not significant explanatory variables with respect to the allocation of time to in-home versus out-of-home activity participation.

Lawson (1996) is conducting dissertation research aimed at modeling the decision to undertake an activity in-the-home or out-of-the-home and explicating the factors that contribute to the decision. She has hypothesized that the explanatory factors include household composition, work characteristics, age composition and lifestyle status. Conceptually, the analysis is based on a utility maximization process, identified in the "new home economics" and applied to the allocation of household resources. Several different choice models will be estimated using the data from the Portland portion of the 1994/95 Oregon-Southwest Washington Household Activity Diary Survey. Lawson plans to capture interpersonal and interactivity effects in her model.

As a third example of recent research in which the relationships between in-home and out-of-home activity participation have been studied, we refer to Lu's (1996) work, which was described in more detail in Section 3.1.3 above. This work, using a structural equation model relating sociodemographics, activity participation and travel, showed clear dependencies between in-home and out-of-home activity participation, as well as the effect of sociodemographics on the decision of whether to spend more time at-home or out-of-home. Thus, for example, an increased number of children in the household was found to increase the time spent on at-home activities and simultaneously decrease the time spent on out-of-home activities. Therefore, the relationship between trip-making and number of children in the household is a rather complex one.

3.2.2 Interpersonal Dependencies

One of the tenets of the activity-based approach to travel modeling is that there are relationships between the activity-travel patterns of members of the same household. Early work at TSU Oxford showed clearly the existence and importance of interpersonal dependencies, and

3.1.6 Summary of Recent Methodological Directions in Activity-Based Modeling

The discussion in this section demonstrates that in recent years there has been a considerable amount of work in the development and application of methodologies for activity-based travel demand modeling. This research and development work is rapidly moving the activity-based approach to travel demand modeling from one in which the primary focus is on descriptive analysis and understanding to one in which forecasting models are being developed and applied.

Some of the methodologies used in the activity-based approach to travel modeling are rather new to the field (e.g., computational process models), while others have seen some previous use in travel demand modeling (hazard-based duration models and structural equation models), and yet others are very familiar to the field (discrete choice models). In addition to providing an overview of the new methodologies, this section also points out that existing modeling approaches are being applied with the insights derived from the rich information base developed by activity-based researchers over the past 20 years.

While there are a number of methodologies being pursued at the present time, in the future researchers will no doubt combine the most appropriate methodologies to develop complete model systems. For example, Hensher (1996) and his colleagues are about to embark on a major research project in which they will develop an activity-based travel demand model system which takes into account travel time budgets, and the duration, sequence and chaining of activities. In this project, the researchers will develop competing risk duration models with generalized logit models to capture the diversity of activity choices and their sequence and duration.

3.2 Phenomena Being Modeled in Recent Activity-Based Travel Models

Many different phenomena are being modeled in current activity-based travel demand modeling work. In some cases, the methodology being used to model a particular aspect of urban activity-travel behavior does not fit into one of the areas discussed in the previous section, in other instances the methodology fails into one of the areas above and the work cited here also appears in the previous section. The purpose of the present section is to give the reader a sense of the range of phenomena being modeled, with a particular emphasis on those phenomena not mentioned in the methodologies section above.

3.2.1 In-Home and Out-of-Home Activity Participation: Trade-Offs and Relationships

The activity-based approach to travel demand modeling focusses attention on the need to be able to model which activities will be undertaken in the home and which will be undertaken outside the home (and thus generate travel), as well as the dependence between time spent at-home and out-of-home. A number of recent activity-based modeling studies have addressed these issues.

Kitamura *et. al.* (1996) formulate a discrete-continuous choice model of time allocation to 2 types of discretionary activities, based on random utility maximization. The model deals with in-transport analysis, it is only relatively recently that we see the development and application of this type of model in the context of activity-based travel demand modeling.

Both Hamed and Mannering (1993) and Bhat (1995) develop and apply discrete-continuous choice models to model post work activity participation behavior, while Kitamura *et. al.* (1996) develop and apply a discrete-continuous choice model to model the allocation of time to in-home and out-of-home discretionary activities (see Section 3.2.1 below). Hamed and Mannering develop a hazard-based duration model to examine home-stay duration after the end of the work day. They estimate a separate logit model of activity type choice, and linear regression equations for travel time to and from the out-of-home activity and the out-of-home activity duration.

Bhat (1995) develops a discrete-continuous model of post home-arrival activity participation behavior in which three inter-related choices are modeled simultaneously, namely (1) choice of next out-of-home activity, (2) home stay duration and (3) duration of the out-of-home activity. The model is estimated, using full-information maximum likelihood, for the case of post-home arrival from work behavior. Bhat's work advances the state-of-the-art in discrete-continuous models in that this is apparently the first case in which full information maximum likelihood has been applied to a discrete-continuous model when the discrete choice is polychotomous. Bhat's methodology also extends previous work by dealing with two continuous outcomes, not one, and it overcomes some of the limitations of Hamed and Mannering's framework.

3.1.5 Enhancement of Existing Travel Demand Models

One approach to improving existing travel demand models, in the short-term, is to make incremental changes to these models based on what we have learned about travel behavior from the activity-based travel research of the past 20 years. One can point to a number of influences that the activity-based approach has had on the development of trip-based, four-step models over the years. The improved specification of travel demand models, especially the incorporation of variables describing household structure (or what is often referred to as "lifecycle") is a good example of the influence of activity-based travel research on traditional travel demand models.

A very good recent example of the use of activity-based research results in making incremental improvements to existing travel demand models is to be found in the current round of model development by the Metropolitan Transportation Commission (MTC) in the San Francisco Bay Area, based on data collected in the 1990 household travel survey conducted in the Bay Area. In this effort, Purvis and his colleagues (Purvis, *et. al.*, 1996) used research on time use to motivate a modification to their otherwise traditional non-work trip generation model. The new non-work trip generation model includes work travel time as an explanatory variable. The idea being that commuters who spend more time on the work commute have less time available to participate in non-work activities. Estimation results confirmed this hypothesis and work travel time was found to have a significant negative effect on non-work trip generation. Purvis *et. al.* (1996) interpret work travel time as a measure of accessibility, thus arguing that improvements in accessibility for the work trip will lead to increases in non-work trip generation and vice versa.

Lu's research shows that complex relationships among socio-demographics, activity participation and travel behavior do exist, and can be captured by the model structure employed in this research. Specifically, Lu and Pas (1997) reach the following overall conclusions. First, significant relationships among socio-demographics, activity participation and travel behavior can be simultaneously captured by the estimated model, and most of the estimated direct effects correspond with the historical findings. Second, travel behavior can be explained better by including activity participation in the model. Third, relationships between in-home and out-of-home activity participation do exist and can be estimated and interpreted. Finally, by examining the direct, indirect and total effects in the model system, we can better capture and understand the relationships among socio-demographics, activity participation and travel behavior, thereby demonstrating the usefulness of structural equations models in modeling the complicated relationships among sociodemographics, activity participation and travel behavior.

3.1.4 Discrete and Discrete-Continuous Choice Models

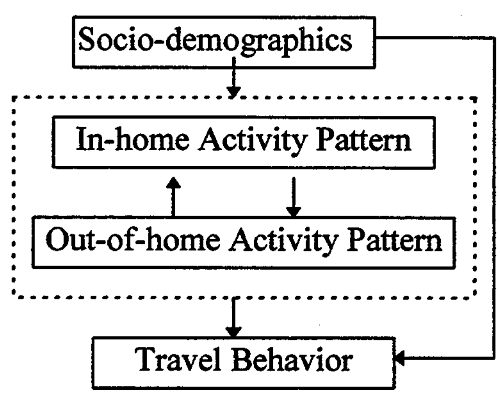
One approach to modeling some of the complexities in travel behavior emphasized by the activity-based approach to travel demand modeling is to use discrete choice or discrete-continuous choice models. Although originally developed and applied in the context of a trip-based framework, discrete choice models have been recently applied to sets of interrelated activities and travel. For example, Ben-Akiva and Bowman (1995) have recently developed a model in which they consider the daily activity-travel pattern as a set of tours. Each tour is assumed to have a primary activity and destination — the primary activity being the major motivation for the tour. Further, tours are sub-divided into primary and secondary tours. The daily activity-travel pattern is thus characterized by a primary activity, primary tour type, and the number and purpose of secondary tours. The tour models, which are conditioned on the choice of a daily pattern, include the choice of time of day (one of four discrete time periods), destination (discrete traffic analysis zones), and mode. The model is operationalized and estimated as a nested logit model, and could be used by an MPO with the capability of estimating a nested logit model. However, the model is quite limited in its spatial and temporal resolution.

Recent work by Bhat (1997) extends the usefulness of discrete choice models by developing a joint model of work mode choice and number of non-work stops during the work commute. Mode choice is modeled using an unordered choice model and number of stops is modeled using an ordered response formulation. The model has been applied to data from the 1990 Boston Area survey, and the results demonstrate the importance of accommodating the inter-relationship between mode choice to work and number of non-work activity stops in the work commute. The results of policy tests with the model show that commuters who make non-work stops on the work commute are unlikely to be drawn away from the drive alone mode.

Another interesting, relatively recent development in activity-based travel demand modeling results from the recognition that discrete choice models, as such, cannot deal with an important variable of interest in the activity-based approach, namely the duration of an activity, because it is continuous in nature. Although it is almost 10 years since Mannering and Hensher (1987) published a review article on discrete/continuous econometric models, and their application to socio-demographics, activity participation and travel behavior, at the individual level, is developed, estimated and interpreted. A complex set of interrelationships among the variables of interest is estimated simultaneously using the structural equation model methodology implemented in LISREL (Joreskog and Sorbom, 1995).

An overview of the model developed and estimated by Lu is shown in Figure 1. This figure shows that activity participation (measured by the duration of activity participation in each of 4 in-home and out-of-home activity categories) and travel behavior (measured by the number of trips, number of trip chains, daily travel time, and percent of trips by car) are *endogenous* to the model (i.e., they are estimated within the model), while socio-demographic characteristics are the *exogenous* variables (or inputs) in this model. The figure also illustrates that the model allows for the *direct* effect of socio-demographics on travel behavior as well as for the *indirect* effect via activity participation (since socio-demographics can affect activity participation which in turn can affect travel behavior). The combination of the direct and indirect effects is known as the *total* effect of one variable on another in a structural equation model.

Figure 1: A Model of Sociodemographics[1], Activity Participation[2] and Travel[3] Model Overview



1 Socio-demographic characteristics included in this model represent household and personal characteristics. Household characteristics include number of workers, number of children, number of vehicles and income, while personal characteristics include age, gender, employment status and license holding.

2 Activity participation is measured by the duration of in-home and out-of-home activities in each of four activity categories.

3 Travel behavior is measured by the number of trips, number of trip chains, daily travel time, and percent of trips by car.

After: Lu and Pas (1997)

activity scheduling as a continuous decision-making process, although further development is needed to deal with some important technical issues.

Bhat (1996a) has recently developed a hazard-based duration model of shopping activity duration on the trip home from work, while at the same time significantly extending the methodology of hazard-based duration models.[5] Bhat (1996b) has also recently developed a multiple durations (i.e., competing risks) model that extends the existing state-of-the art considerably. Thus, there are a number of recent examples of the application of hazard-based duration models to activity duration modeling and examples of methodological developments as well.

3.1.3 Structural Equation Models

Structural equation models have been applied in a number of areas of the social sciences for quite some time. This methodology has seen relatively little application in travel demand modeling in spite of its ability to facilitate the modeling of a large number of interrelated variables. Up until very recently, all the work in the application of structural equation models to travel demand modeling was conducted by Golob, who pioneered the use of this methodology in travel demand modeling, and his collaborators (see, for example, Golob and Meurs 1987; Golob 1990a, 1990b). However, other researchers have recently started using the structural equation models methodology to develop activity-based travel demand models (Fujii et. al, 1996; Lu, 1996), and Golob has extended the range of applications to which he has applied this methodology to include activity-based travel demand modeling (Golob, 1996; Golob, Bradley and Polak, 1996; Golob and McNally, 1995).

The current applications of structural equation models to travel demand make use of the methodology to capture some of the complex relationships considered important in the activity-based approach to travel demand. Fujii *et. al.* (1996), for example, use the methodology of structural equation models to model commuters' time use and travel after work hours using data collected in the Osaka-Kobe metropolitan area. Their model shows that of a 10-minute time "savings" for the commute trip, slightly more than 7 minutes will be used for in-home activities, thus bringing into question the idea of a constant travel time budget.

Golob and McNally (1995) develop a joint model of the out-of-home activity participation and travel of male and female couples (whether they are spouses or not) who are heads of households (see Section 3.2.2 below for more detail on this work). Golob (1996) uses the structural equation modeling approach to model demand for activity participation and mobility, and he includes one category of in-home activity (namely, work) in the model. The model is formulated to allow for a number of hypothesized behavioral phenomena including: travel demand derived from activity participation, time budget effects, mobility demand (activity participation affects vehicle ownership), and accessibility (vehicle ownership affects activity participation).

One recent application of the structural equation modeling methodology to activity-travel relationships is the work of Lu (Lu, 1996; Lu and Pas, 1997). In this work, a model relating accident, and vehicular delay at international border crossings) and travel behavior. Applications referenced by Hensher and Mannering in the latter area include the length of time travelers delay their departure from work in order to avoid congestion (Mannering and Hamed, 1990), the time travelers stay at home between activities requiring trips (Mannering *et. al.*, 1992 and Hamed *et. al.*, 1992), and the time until acceptance of a new tolled roadway (Hensher and Raimond, 1992).

The general idea of a hazard-based duration model is that it tries to model the conditional probability of "failure" at time t (i.e., the probability that the event of interest terminates at time t), given that failure has not occurred prior to this time (i.e., that the event has not terminated prior to time t).[4] Thus, for example, one might try to model the probability that a worker finds a job at time t (ending the unemployment period), given that s/he is unemployed up to this time.

The most relevant application of the hazard-based duration model in activity-based travel demand modeling is in connection with modeling the duration of activities and home-stay duration (time between returning home and leaving on another trip). In this connection, the most pertinent work is that of Neimeier and Morita (1996), Mannering and his associates (Mannering *et. al.*, 1992; Hamed *et. al.*, 1992), Ettema *et. al.* (1995) and Bhat (1996a, 1996b). However, another possible use of hazard-based duration models is in modeling the time until the next activity of a particular type occurs. Thus, with the appropriate data, one could model the time between, say, shopping activities.

As noted earlier, Mannering *et. al.* (1992) and Hamed *et. al.* (1992) have applied hazard-based duration models to model the length of time a traveler spends at home before making another trip. Specifically, this work deals with the amount of time a commuter spends at home after arriving home from work before leaving home to take part in another out-of-home activity. Neimeier and Morita (1996) developed a model for the duration of particular trip-making activities based on gender. The activities they studied include: household and family support shopping, personal business, and free time. Neimeier and Morita found no significant differences between the durations of men and women for the free-time and personal business activities, but gender was a very significant explanatory variable in the case of the household and family support shopping activities, with women being more likely than men to have longer durations for household and family support shopping activities. Hazard-based models have also been used to study the time that a car is stationary, with respect to being able to predict the probability of a cold-start (Ponnoluri, 1995).

A recently developed duration model, developed by Ettema *et. al.* (1995), deals with both activity duration and activity choice by using what is known as a "competing risk" hazard model. The authors estimated the model using data collected from a small sample of students, through an interactive computerized data collection procedure called MAGIC, which they have developed to investigate activity scheduling behavior (Ettema *et. al.*, 1993). The estimated model parameters show that spatio-temporal constraints such as time of day, opening hours and travel time, play an important role in activity scheduling. Activity duration and type were also found to be dependent on the history of the activity-travel pattern and the traveler's priorities. The authors conclude that the estimated model performs satisfactorily, and holds promise for describing could be used to forecast commuters' short-term responses to the type of TCM measures being considered in the MWCOG region. Six policies were included in the study, as follows: (1) parking pricing, (2) improved bicycle and pedestrian facilities, (3) a combination of (1) and (2), (4) parking pricing with employer commuter voucher, (5) congestion pricing, and (6) a combination of (4) and (5).

This project used a 3-phase survey to collect information about the respondents' sociodemographic characteristics, their commute characteristics, their time use for a 24-hour period, and their stated response to the set of TCM measures listed above. The stated response section of the survey was customized to each commuter's work or school trip, in terms of the commute distance and travel time, and respondents were asked how they would respond to each TCM in the context of their activity and travel behavior on the previous day. The responses were coded into one of eight categories, as follows: do nothing, change departure time to work, change mode to carpool, change mode to transit, change mode to walk, change mode to bicycle, work at home, and other (e.g., long term changes). The stated response data was used to "train" (calibrate) a neural network to predict commuters' basic responses to the TCM measures, using sociodemographics, land use, transportation network and TCM characteristics. The calibrated AMOS model was applied to a small sub-sample of commuters from the 1994 MWCOG household travel survey, to predict the impacts (including the percent of cold starts) of the alternative TCMs.

In addition to AMOS, there are a number of other CPM's that have recently been developed or are currently under development. These models include SCHEDULER (Gärling *et. al.*,1989; Golledge *et. al.*, 1994), SMASH (Ettema *et. al.*, 1995b), and PCATS (Kitamura, 1996). Furthermore, in his development of an activity-based CPM of travel behavior, Vause (1995) is making a valuable contribution by developing techniques to assist in the formulation of the rule base used in the CPM.

3.1.2 Hazard-Based Duration Models

Hazard-based duration models were originally developed for, and applied to, problems in the fields of medical science and industrial engineering, but they have also seen extensive application in economics (primarily labor economics) and marketing. Since the late 1980's, hazard-based duration models have also been applied to a number of transportation-related phenomena, including travel demand. Hensher and Mannering (1994) provide a thorough review of the important concepts in hazard-based duration modeling and examples of the application of these models to transportation phenomena. They argue that hazard-based duration models provide the transport modeler with a powerful tool and they note that there have been surprisingly few applications of these models in transportation modeling, especially since transportation modelers routinely deal with duration-related phenomena.

Hensher and Mannering (1994) include in their review example transportation applications in the areas of accident analysis (time between accidents), car ownership modeling (time between households' vehicle purchases), traffic operations (time to restore a freeway to capacity after an developed by Newell and Simon (1972). A production system model attempts to capture the decision-making process using a set of rules in the form of condition-action pairs.

The key point about CPM's is that such models attempt to represent explicitly the process used by the individual to make a decision, whereas in our conventional approaches to travel demand modeling, e.g., discrete choice models, the decision-making process is implicit in the model formulation. Computational process models allow for a variety of decision-making strategies, and allow the decision-making strategy of an individual to be different in different circumstances, while recognizing the human's limited information processing ability. Golledge *et. al.* (1994) note that CPM's have been developed in an attempt to "... replace the utility maximizing framework with behavioral principles of information acquisition, information representation, information processing, and decision making". They also point out that "... appropriate statistical techniques for estimating and calibrating CPM's are yet to be defined", but it should be noted here that some of the rules in a production system model can be based, for example, on discrete choice models.

Gärling *et. al.* (1994) discuss production system and computational process models and review the application of such models to activity scheduling behavior (including activity type, duration, sequencing, location and mode of travel). A number of CPM's are reviewed in their paper, including those dealing with information acquisition and representation in the context of navigation and route choice, as well as in the context of interrelated activity and travel decisions. CARLA (Jones, *et. al.*, 1983) and STARCHILD (Recker et. al, 1986a, 1986b) are the two early examples of such CPM-type models. CPM's have been applied primarily to the scheduling and rescheduling problems. In these models, the set of activities to be performed is generally taken as given. Recently, Pas (1996) suggested that CPM's might also be useful for the development of activity generation models if such models are to attempt to represent the process of activity generation.

One CPM has recently been applied in the U.S.A. at the metropolitan area level, in prototypical form. This model, known as AMOS (Activity-Mobility Simulator), is a component of the SAMS (Sequenced Activity-Mobility Simulator) model (Kitamura *et. al.*, 1996). The latter model was conceived by the RDC, Inc team in the FHWA-sponsored project "Redesigning the travel demand forecasting process" (RDC, 1993). The SAMS model is an integrated simulation model of land-use, sociodemographics, vehicle transactions, activity-travel behavior, network performance and air quality. The AMOS model, which is at the heart of the SAMS model, is described briefly below as an example CPM that has been applied to a real-world policy analysis situation.[3]

The AMOS model is an activity-based CPM that focusses on travelers' adaptation to policy changes. A prototype version of the AMOS model, designed specifically to deal with short-term responses to transportation control measures (TCMs), has been developed and applied in the Washington, DC area in a project sponsored by the FHWA and the Metropolitan Washington Council of Governments (MWCOG) (see RDC, 1995, for a detailed description of this project and the results obtained). The development and application of the AMOS model in the Washington, DC area was designed to demonstrate how an activity-based travel demand model

This research provides a very solid base on which the next generation of travel demand models is currently being built, as we now have a much better understanding of the phenomenon we are trying to model.

The interested reader can consult a number of review articles for additional, different perspectives on the activity-based approach to travel demand modeling, ranging from the early review prepared by Damm (1983), to the more recent reviews prepared by Kitamura (1988), Jones *et. al.* (1990), and Axhausen and Gärling (1992). For a recent discussion of the contribution of the activity-based approach to transportation policy analysis see Jones (1995), and for another perspective on the activity-based approach see the paper by Kurani and Lee-Gosselin (1996) in this volume. For an assessment of recent developments in household activity scheduling and the prospects for the future, see Kurani and Kitamura (1996).

3. RECENT AND CURRENT DIRECTIONS IN ACTIVITY-BASED TRAVEL DEMAND MODELING

In this section of the paper we discuss recent and on-going advances in activity-based travel modeling, This review is not intended to be comprehensive, but it does attempt to cover all the relevant directions being followed. The purpose of the review is to illustrate the directions being taken, and to show that advances are being made, not to provide a detailed account of recent and current research in any of the areas discussed here. This review is organized in terms of the methodologies being used and the phenomena being modeled, and we have attempted to include all the relevant methodologies being used and the phenomena being modeled, while providing a representative sample of work in each area covered.

3.1 Methodological Advances in Activity-Based Travel Modeling

One can readily identify a number of methodological areas in which advances have recently been made, and continue to be made, in the area of activity-based travel demand modeling. Some of these methodologies have been applied to travel demand modeling only recently, while other methodologies have seen application over a longer time period, but the phenomena to which they are being applied currently are new. The newer methodologies include computational process models, hazard-based duration models, and discrete-continuous choice models, while discrete choice and structural equation models are now being applied to a wider set of phenomena than in the past. These areas of methodological advancement are discussed in the sub-sections below.

3.1.1 Computational Process Models

One of the most interesting, and potentially powerful, new directions in activity-based travel modeling is the development and application of what are usually termed computational process models (CPM's). Such models are computerized implementations of what are known as production system models, which trace their origins to models in the psychology literature that appear to produce acceptable forecasts. Proponents of this approach believed that one needed to have a good understanding of the behavioral phenomenon being modeled in order to develop sound predictive models. Much of the early work on the activity-based approach to travel demand analysis used in-depth interviews, with small samples, in an attempt to gain a good understanding of urban travel behavior. In particular, the HATS methodology (Jones, 1979), essentially a gaming simulation, was used very successfully by the researchers at TSU, Oxford, in trying to gain a better understanding of household level travel decisions and the constraints within which those decisions are made.

An early paper in the activity-based travel modeling literature by Heggie (1978), entitled "Putting Behaviour into Behavioural Choice Models", argued that urban travel behavior is a complex phenomenon that could not be suitably represented in the discrete choice models (specifically logit models) that were gaining considerable popularity at the time the foundations of the activity-based approach were being put in place. Essentially, Heggie argued that while the discrete choice modeling framework provides a sound and rigorous approach to modeling the choice of an alternative from a set of available alternatives, the behavior being modeled at that time, primarily mode choice for the work trip, was not the correct behavioral phenomenon. In other words, a good tool was being used to address the wrong problem[2]. Most importantly, the discrete choice models that were being developed at that time, and that have dominated the field until recently, were not designed to be able to take account of dependencies among trips and between people, nor to account for constraints on activity participation and travel behavior.

The activity-based approach to travel demand forecasting can be considered the only real scientific revolution or paradigm shift, in Kuhnian (1970) terms, in the history of the development of travel demand forecasting models. The shift from aggregate to disaggregate models that took place starting in the 1970's was a shift in statistical technique rather than a shift in the paradigm and thus can be considered an incremental change in the approach to travel demand modeling (for further discussion of this point, see Pas, 1990).

The activity-based approach to travel demand analysis encompasses many theoretical concepts and methodologies. However, the themes of the approach can be clearly discerned in the large body of activity-based travel demand research. In 1985 Pas described these themes as follows: (a) analysis of demand for activity participation (and the analysis of travel as a derived demand), (b) the scheduling of activities in time and space, (c) the constraints (spatio-temporal and interpersonal) on activity and travel choice, (d) the interactions between activity and travel choices over the day (or longer time period), as well as interactions between individuals, and (e) the structure of the household and the roles played by the household members. To this list, we should now add dynamics and adaptation to change as themes of the activity-based approach. Furthermore, as Kurani and Lee-Gosselin (1996) note, time use is becoming the focus of much activity-based research. (For an introduction to time use studies and their relationship to travel demand modeling, see Pas and Harvey, 1991, and for a more recent review, see Pas, 1996).

As noted above, much of the past effort in the activity-based approach to travel demand analysis and modeling has been devoted to developing a better understanding of the phenomenon of urban travel behavior, with less effort devoted to the problem of modeling and predicting this behavior.

ready for implementation at a time when the planning and policy analysis issues of the day cannot be suitably addressed by the existing, trip-based, four-step travel demand model.

The objective of this paper is to identify and document recent advances in activity-based travel demand modeling, while setting these advances in the context of the considerable history of development in activity-based approaches to travel modeling. The review of recent advances in activity-based travel modeling is organized in terms of the methodologies being developed and used and the phenomena being modeled. The review is not intended to be exhaustive in terms of the works described and cited, but it is intended to include a representative sample of recent and on-going work in the field in order to demonstrate the type and the extent of the advances being made.

The remainder of the paper is organized as follows. In the second section, we provide some background on the activity-based approach to travel demand analysis and modeling — readers already familiar with the development of this approach can readily skip this section. The third section of the paper provides an overview of recent advances in activity-based travel modeling, while the fourth section provides a brief discussion of the reasons that the activity-based approach to travel demand modeling has seen considerable progress of late. The final section of the paper presents some concluding thoughts.

2. BACKGROUND

The activity-based approach to travel demand analysis is founded on the well-known and long-accepted idea that travel is generally not undertaken for its own sake but rather to participate in an activity at a location that is separated from one's current location. The idea that travel is a derived demand has been accepted by travel demand modelers ever since it was first articulated by Oi and Shuldiner (1962) in their seminal work on urban travel demand. However, traditional travel demand models pay only lip service to this fundamental idea by segmenting trips by trip purpose and modeling the trips for different purposes separately.

The activity-based approach to travel demand analysis and modeling traces its roots to the seminal work on urban travel demand analysis undertaken in the mid to late 1970's at the Transport Studies Unit (TSU) at Oxford University under the leadership of Ian Heggie, working under a grant from the Social Sciences Research Council (Jones, *et. al.*, 1983). The activity-based approach was founded on the work undertaken previously by the sociologist and planner, F. Stuart Chapin Jr., at the University of North Carolina at Chapel Hill (Chapin, 1974), and by the geographer Torsten Hagerstrand at Lund University in Sweden (Hagerstrand, 1970, 1972). Kurani and Lee-Gosselin (1996) note that Chapin's work contributed by identifying patterns of behavior across time and space, while Hagerstrand's work delineated systems of constraints on activity participation in time-space. It is important to note the clear influence of fields other than economics in the development of the activity-based approach to travel demand analysis[1].

The development of the activity-based approach to travel demand analysis is characterized by a desire to *understand* the phenomenon of urban travel, not merely to develop predictive models

RECENT ADVANCES IN ACTIVITY-BASED TRAVEL DEMAND MODELING

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ABSTRACT

This paper presents an overview of recent and on-going advances in activity-based travel demand modeling, organized in terms of the methodologies employed (including computational process models, structural equation model systems, and hazard-based duration models) and the phenomena being modeled (including in-home and out-of-home activity participation, interpersonal dependencies, and daily activity-travel patterns). The paper sets the overview of the recent and on-going advances in activity-based travel modeling in the context of the long and rich history of activity-based travel analysis, which was first proposed about 20 years ago as an alternative to the trip-based modeling framework and the discrete choice, utility-maximizing models that were being incorporated into the trip-based travel demand modeling framework at that time.

This paper finds that substantial progress has been made recently, and continues to be made, in advancing from activity-based travel analysis (with an emphasis on descriptive analysis and understanding), to activity-based travel forecasting models that can be used effectively for addressing contemporary policy and planning issues. The considerable recent effort and progress in activity-based travel modeling is attributed to technical, institutional and data availability factors.

1. INTRODUCTION

Twenty years ago, researchers at the Transport Studies Unit at Oxford University began seminal work in the development of an alternative travel demand modeling paradigm to the trip-based, four step modeling approach that was first developed during the early metropolitan land-use/transportation studies conducted in the U.S.A. in the mid to late 1950's. The alternative paradigm became known as the activity-based approach because it is based on the well known and long accepted idea that travel is a demand that arises through people's needs and desires to participate in activities. After many years of development, the activity-based approach to travel is

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1. For each Public Use Micro Area (PUMA) construct the multi-way distribution of attributes from the corresponding PUMS.
2. A two-step iterative proportional fitting (IPF) procedure is used to estimate simultaneously the multi-way distributions for each census tract within a PUMA, such that each distribution satisfies the marginal distributions for the census tract (as defined by aggregate census tables) **and** has the same overall correlation structure as the PUMS-based multi-way distribution. This IPF procedure can be interpreted as the constrained maximum entropy estimate of the multi-way distribution given the known information and the available PUMS data.
3. Individual households are then randomly drawn **from the full multi-way distribution** for each census tract.

The TRANSIMS procedure is relatively straightforward to implement and appears to perform well in validation tests to date [Beckman, *et. al.*, 1995]. In particular, it clearly performs better than either drawing households directly from the PUMS multi-way distribution (i.e., without "filtering" this distribution through the census tract marginal distributions by means of the two-step IPF procedure) **or** drawing households directly from the tract marginals (i.e., a simplified version of the Wilson and Pownall procedure). While more operational experience is obviously required with population synthesis methods, the general thrust exemplified by the TRANSIMS approach appears to be well founded: use a "full information" approach which accounts for multi-way correlation among the attributes being synthesized.

4.2 Population Updating

Once the base year population has been provided to the model, either through a survey sample or a synthesis procedure, this population must be "updated" each time step within the simulation run. The nature of this updating obviously depends on the attributes involved, the processes being simulated, the size of the simulation time step, etc. Assuming, however, that one is simulating household processes over a number of years, in one year time steps, demographic and socio-economic processes which need simulating as part of the updating process may well include:

- aging;
- births and deaths;
- marriages and divorces;[13]
- other changes in household structure (adult children leaving the home, etc.);
- non-family household formation and dissolution;
- changes in education level;
- changes in employment status (entry/exit to/from the labor market, change in job location and/or type, etc.);

[13] Generally these terms are used to represent the more generic processes of "couples" forming and dissolving, whether or not actual marriages and divorces occur.

- changes in residential location;
- changes in automobile holdings (types and numbers of vehicles); etc.

With the exception of aging, which is a completely deterministic accounting process, each of these processes require a sub-model of some sort. Demographic and household structure attributes are generally handled using very simple probability models: either fixed transition rates based on empirical data (e.g., fertility rates for women by age group), or simple parametric probability functions (e.g., MIDAS uses simple logit models to determine household type transition probabilities). In all such cases, Monte Carlo simulation methods are used to generate household-specific "events" (birth of a child, etc.) on a household-by-household and year by year basis.

Treatment of employment status, residential location and automobile holdings varies far more widely across models, depending on their application. Each of these can be a significant part (or even the primary focus) of the behavioral modeling component of the microsimulation (see Section 5). Alternatively, if the application permits, one or more of these might be handled in terms of "transition probabilities" in the same way as the demographic variables discussed above.

As with synthesizing procedures, limited experience exists, at least within the travel demand forecasting community, with demographic/socio-economic updating methods. For examples of specific methods used to date, see, Miller, *et. al.* [1987], Kitamura and Goulias [1991], Goulias and Kitamura [1992], and Oskamp [1995]. All of these examples should, I believe, be treated as being illustrative and experimental in nature rather than in any way definitive in terms of "the" method to use. Considerable experience with demographic forecasting obviously exists among demographers. Traditional demographic forecasting, however, does not attempt to work at the fine spatial scale required by our travel demand forecasting applications. Our challenge is to adapt existing methods and/or develop new ones which can operate reliably at the census tract/traffic zone level required for travel demand forecasting.

5. EXAMPLE APPLICATIONS

Much of the travel-related microsimulation modeling which has been undertaken to date has occurred in application areas other than activity-based modeling *per se*. These application areas include: auto ownership, residential mobility, and dynamic network assignment. Sub-section 5.1 briefly reviews representative models from these application areas, with emphasis on their relationship to activity/travel demand modeling. Section 5.2 then briefly discusses examples of activity-based microsimulation modeling.

5.1 Miscellaneous Application Areas.

1. Microsimulation of auto ownership. Some of the earliest applications of microsimulation in the transportation field involved dynamic modeling of auto ownership (e.g., Barnard and Hensher [1982] and Daly [1982]). Behavioral modeling of auto ownership has almost always occurred as a "stand alone" activity, outside of the "normal" activity/travel demand modeling process.[14] Within the travel demand modeling process, auto ownership has typically been treated as just one socio-economic "exogenous" input to the demand process. For some purposes this may be adequate, in which case a "transition probability" treatment within a microsimulation modeling system would be adequate. Many current policy issues, however, (notably concerning emissions and energy use) relate in no small way to household decisions concerning the number and types of vehicles which they own, as well as on the interactions between vehicle holdings and (auto) travel demand. Thus, a strong case exists for including explicit models of household automobile choice within the overall travel demand modeling process [Miller and Hassounah, 1993].

2. Microsimulation of housing markets and residential mobility. Many of the microsimulation models developed to date fall into this general category. Early work includes that undertaken by Wegener [1983], Mackett [1985, 1990] and Miller, *et. al.* [1987]. This continues to be an active area for research efforts, including work by Spiekermann and Wegener [1993] and Oskamp [1995].[15]

Given the central role which lifecycle stage and household structure play in determining residential mobility, these models typically deal in detail with population and household synthesis and updating -- issues of considerable importance to activity-based models (and ones which have already been dealt with in Section 4). In addition to the technical issues relating to synthesis and updating already discussed, note that the discussion to this point in the paper has been relatively indifferent to the "unit of analysis" within microsimulation models. In residential mobility modeling it has long been recognized that both households and persons (with the later being further sub-divided into workers, non-workers, etc.) must be maintained within the modeling system, given that some decisions are inherently household-level in nature (e.g., residential choice), while others inherently occur at the level of the individual (e.g., change jobs), with interactions between both levels continuously occurring[16] (e.g., the decision to change jobs may have ramifications for household income levels and hence the suitability/affordability of the current residential location; the decision on whether/where to move may be influenced by the impact which the move would have on commuting times and costs). As a result, such models generally maintain both households and persons (and mappings between the two) as explicit elements of their database. This dual representation presumably will prove useful to activity-based models, both as they move to more household-level formulations and as they become more integrated with residential mobility models within more comprehensive microsimulation frameworks.

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[14] MIDAS [Goulias and Kitamura, 1992], discussed below, represents a notable exception in this regard.

[15] Work in this area is also proceeding by a collaborative team of Canadian researchers from the University of Toronto, McMaster University, Laval University and the University of Calgary. This project is in a very preliminary stage at time of writing and has yet to publish results.

[16] See, for example, Birch, *et. al.* [1974].

In addition, of course, housing market models are intended to forecast medium- to long-term evolution of the spatial distribution of the residential population, another key input into activity-based models. Considerable debate currently exists, particularly within the United States, concerning "land use - transportation interactions", the nature and extent of "induced demand", etc. Development of credible, integrated models of residential (and employment) location processes and activity/travel demand seems to me to be a particularly important step towards investigating the medium- to long-term impact of both land use and transportation system policies and hence towards contributing in a analytically sound way to this extremely important policy debate.

3. Microsimulation of auto route choice and network performance. As mentioned briefly in Section 3, many current and emerging road network assignment procedures are microsimulation-based (e.g., Barrett, *et. al.* [1995], Hu and Mahmassani [1995], Mahmassani, *et. al.* [1994]). A detailed review of these procedures is well beyond the scope of this paper. Three points to note about these models, however, are:

i) As has already been discussed Section 3, the input requirements of these network microsimulation models may in some instances drive the design criteria for activity-based travel forecasting models. TRANSIMS is perhaps the best example of this point, in that the network performance/emissions modeling needs are clearly in this case driving the overall system design.

ii) The "interface" between the activity-based models and the network models generally does not simply consist of the outputs from the one becoming the inputs to the other. Typically, dynamic route assignment procedures simultaneously determine route choice and trip departure time choice (given assumptions about desired arrival times). DYNASMART perhaps best typifies operational capabilities in this regard. Thus, these models "intrude" into at least one component of the activity-based modeling domain: the "micro-scheduling" of trips. Again, this may well have design implications for activity-based models to the extent that they are intended to be integrated with network microsimulation models.

iii) Most current network microsimulation models appear to have been developed with short-run (and, in some cases, real-time) forecasting applications in mind, often specifically relating to ITS applications. Whether these models are well suited for medium- to long-term forecasting applications is, I believe, an unanswered question at this point in time. Issues include the level of detail of network representation often required by these models (e.g., are we able to specify the traffic signal settings and offsets twenty years into the future, as may be required by some models), as well as the match between network model precision (e.g., second by second calculations of individual vehicles' performance) and the accuracy of the activity/travel demand model's predictions (even with microsimulation!), given the inevitable uncertainties associated with medium- to long-term forecasting.

5.2 Activity-Based Microsimulation Models

Given the inherently disaggregate nature of activity-based models, as well as the fact that these models typically incorporate some level of dynamics, one might argue that a large portion of the extensive activity-based modeling literature should be included in this section.[17] This has not been attempted here. Rather emphasis has been placed on including models which emphasize the connection between activity modeling and travel demand forecasting in at least a quasi-operational manner, and which do this within an explicit microsimulation framework.

Bonsall [1982] provides a very early example of the application of microsimulation to the problem of predicting commuters' participation in a proposed ridesharing program. Although very specialized in nature, the model is noteworthy given its time period of development, as well as for the clarity with which the paper discusses general issues of microsimulation modeling.

Axhausen [1990] reports on a considerable "tradition" in Germany of activity-based microsimulation modeling of destination and mode choice, tracing back to Kreibich's initial work in the late 1970's [Kreibich, 1978, 1979]. Much of this German work has been generally inaccessible to North American audiences since, with the exception of Kreibich's papers, most of it has only been published in German. Axhausen's contribution was to combine an activity chain simulation model (which had been the focus of the work of Kreibich, *et. al.*) with a mesoscopic traffic flow simulator.[18] This paper is noteworthy in at least two respects. First, it represents an early attempt to link an activity-based model directly to a network assignment model -- clearly an essential step in developing a true activity-based travel demand forecasting capability. Second, the decision to use a mesoscopic rather than microscopic traffic simulator provides a useful counterpoint to the general North American trend of leaping directly to the extreme micro level for this later type of model.

MIDAS (Microanalytic Integrated Demographic Accounting System) [Kitamura and Goulias, 1991; Goulias and Kitamura, 1992, 1996] represents an extremely important milestone in the development of transportation-related microsimulation models. Developed for the Dutch government, MIDAS is an operational microsimulation-based forecasting tool. Starting with a nationwide sample of households obtained from the Dutch Mobility Panel, the model has two main components: a socio-economic and demographic component which simulates household transitions, including births, deaths, household type changes, as well as changes in persons' employment status, personal income, driver's licence possession and education; and a "mobility component" which simulates auto ownership, trip generation and modal split. Although the

[17] Very explicitly simulation-based activity-based models such as STARCHILD [Recker, *et. al.*, 1986a, 1986b] and the simulation model developed by Ettema, *et. al.* [1993] particularly come to mind.

[18] Mesoscopic network models generally work at the level of the individual vehicle, but make use of much more simplified models of vehicle performance than the microscopic models discussed above. For a detailed discussion of the potential merits of mescopic models, see Miller and Hassounah [1993].

application is somewhat atypical (i.e., predicting overall national travel levels rather than intra-urban trip-making), the model contains most of the attributes of the activity-based travel forecasting microsimulation modeling "paradigm" presented in Section 2 of this paper. In particular, the model's treatment of the demographic and socio-economic updating problem is very strong.

In 1992 FHWA commissioned four groups (RDC, Inc., Caliper Corporation, MIT, and the Louisiana Transportation Research Center — LTRC) to propose new modeling systems to replace the conventional four-stage system. It is noteworthy that two of the four groups (RDC and LTRC) proposed activity-based microsimulation designs, while a third (MIT) proposed a disaggregate activity-based approach which certainly could be implemented within a microsimulation framework [Spear, 1994]. Further, both RDC's SAMS (Sequenced Activity-Mobility System) and LTRC's SMART (Simulation Model for Activities, Resources and Travel) postulated an integrated, comprehensive modeling system beginning with land use and flowing through activity/travel decisions to dynamic assignment of vehicles to networks (and hence calculation of congestion, emissions, etc.).

Since the FHWA study, a prototype of AMOS (Activity-Mobility Simulator), the central component of the proposed SAMS system, has been developed and used in Washington, D.C. to evaluate alternative TDM strategies [RDC, 1995]. Within the context of this paper, AMOS represents an example of an activity-based travel microsimulator. As currently implemented, it represents a stand-alone tool for analyzing a specific type of short-run transportation policies which is not currently tied to either a demographic simulator (as in the case of MIDAS) or a network simulator (as in the case of Axhausen's model). More generally, however, it represents a potential stepping-stone towards a more comprehensive microsimulation system such as SAMS which would include these other microsimulation components, among others.

Finally, TRANSIMS [Barrett, *et. al.*, 1995] represents by far the most ambitious attempt to date to develop a comprehensive microsimulation travel demand forecasting model. The TRANSIMS program is well documented in the literature, as well as in other presentations at this conference, and so no attempt will be made in this paper to provide a complete description of the model. From the point of view of this paper it is perhaps sufficient to observe that the TRANSIMS work is at the present time both defining much of the state-of-the-art in microsimulation modeling and challenging other researchers to develop their own thoughts and models. Regardless of the extent to which TRANSIMS *per se* ever becomes an operational planning model, the impetus which it has provided to the development of microsimulation models and to the evolution of travel demand modeling in general is of considerable importance.

6. RESEARCH & DEVELOPMENT ISSUES AND DIRECTIONS

With the exception of MIDAS (and, possibly, AMOS), virtually all travel demand-related microsimulation models developed to date must be classed as "prototypes", designed to demonstrate the feasibility of microsimulation and/or to investigate very specific policy questions. Moving microsimulation "out of the laboratory" and into operational practice will require considerable additional research and development. Some of the key issues, in my opinion, which need to be addressed in this R&D effort include the following.

1. Continued development and testing of population synthesizing and updating methods. Just as conventional four-stage models depend fundamentally on the population and employment inputs provided to them, so the microsimulation systems envisioned within this paper depend on the population demographic and socio-economic "inputs" to the behavioral components of the model. While the TRANSIMS procedure for population synthesis appears very attractive (and emerges out of at least twenty years of experience in the literature with related but simpler methods), clearly much more operational experience is required before such a method can be considered a proven tool. Updating methods similarly have clearly been demonstrated to be feasible but require much further incremental experimentation, improvement and "optimization".

2. Determination of appropriate levels of aggregation. Even in a microsimulation model, aggregation inevitably occurs. Aggregation can occur in space (typically through the use of zones as the spatial unit of analysis, even when modeling individual decision-makers within these zones), time (primarily in terms of the time step used to move the model through simulated time: a model which operates on a one-year time step is temporally more aggregate than one which steps through time on a month by month basis), attributes (no matter how detailed the model's description of an individual, there is always some point beyond which two individuals will be considered "identical"; individuals are, however, exactly that, and by treating them as identical we are, in fact, introducing some amount of aggregation into the analysis[19]), and behavior (e.g., perhaps in a given model all types of non-grocery shopping — everything from buying shoes to buying a new car — might be aggregated into a single activity category).

A major rationale for the disaggregate modeling approach is the minimization of aggregation bias. In the theoretical development of our disaggregate models it is often easy to pretend that these models truly operate at the level of unique individuals acting within their actual individual choice contexts. It must be recognized, however, that **any** operational model will inevitably reach some finite limit of disaggregation (where this limit may be defined by data availability, theoretical insight, methodological capabilities, computational feasibility, and/or application requirements), beyond which aggregate "homogeneity" assumptions are inevitably required. This is neither good nor bad, but rather simply a fact of model building. The key point is to recognize this fact and to make intelligent decisions concerning where finer levels of disaggregation are both **required** and **achievable**, and where more "aggregate" representations either can be used because of the nature of the problem (relative homogeneity does exist, system state estimates are robust with respect to this component of the model, etc.) and/or must be used due to inherent limitations in our modeling capabilities.

Over and above a general concern with finding appropriate levels of disaggregation in our microsimulations, specific issues include:

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[19] Section 4 discussed this same issue in terms of the use of a sample of individuals, in which case each sampled individual inevitably ends up represented an aggregate group of "similar" individuals within the model.

i) **Treatment of space.** Many activity-based models developed to date are surprisingly "aspatial". If such models are to be practical travel demand forecasting tools they must ultimately be able to generate auto, transit, walk, etc. trips from point to point in space. Or is it zone to zone in space? Considerable uncertainty currently exists about what level of spatial disaggregation is required to support forecasting requirements for emissions analysis, etc. Nor is it currently clear what level of spatial disaggregation is likely to be supportable with respect to data and computational capabilities, even given modern Geographic Information Systems (GIS), etc.

ii) **Treatment of time.** Different urban processes operate within very different time frames. Residential and employment location processes operate over periods of years, typically involving brief periods of intense activity (e.g., looking for a new home or job), followed possibly by decades of inactivity. Most demographic process operate on approximately a yearly scale. Activity/travel decisions, however, occur more typically within daily or weekly time frames. Tailpipe emissions from a vehicle depend critically on the second-by-second decisions of the vehicle's driver.

Within each of these components of the overall travel demand process decisions need to be made concerning the best time step to use in modeling the given component. Is second-by-second simulation of vehicle performance really necessary or can a longer time step (say 5 seconds) be used? Is the day or the week the "fundamental" step in modeling household activity and travel dynamics (or is hour-by-hour or minute-by-minute simulation required)? Can one year time steps by used to simulate residential mobility decisions (and if so, how does one handle the "microdynamics" of the housing search process which typically occurs over a period of a few weeks or, at most, months)?

These questions become even more problematical as one attempts to bring these model components into a comprehensive modeling system. It is easy to speak about the need for integrated land use - transportation models, for example, but how does one actually integrate these models, given their very different time frames?

iii) **Selection of attributes.** Models vary in terms of the definition and detail of the attributes of persons, households, etc. being modeled. Decisions concerning these attributes obviously affect, among other components of the model, the nature of the population synthesis and updating procedures required to generate and update these attributes over time. Tradeoffs may well often occur between the ability of the synthesis/updating procedures to reliably provide a given attribute and the relative importance of the attribute within the behavioral model.

3. Linkages among model components. As has been mentioned at various points throughout this paper, linkages between location choice, activity/travel decisions and network assignment and performance models represent both a trend and a desirable feature in microsimulation model development. In particular, analysis of the full range of possible impacts of a given policy may often require a relatively comprehensive modeling system, given the wide range of possible short-run and long-run responses available to individuals and households in many cases.

While conceptually attractive, comprehensive microsimulation models obviously bring with them a host of model design issues, not the least of which is the computational feasibility of such models. It is to be expected that many modelers will continue to develop individual models for various components of the overall process, both as a means for best making progress in the development of these components, and as a means for analyzing problems directly addressable by such models. At the same time, other modelers will continue with the task of developing comprehensive modeling systems, often with simplified versions of the current state-of-the-art component models. Both types of activities obviously are mutually reinforcing and are to be encouraged.

4. Demonstration of the statistical properties of microsimulation models. Almost all microsimulation models include stochastic elements. Surprisingly little attention seems to have been paid to the statistical properties of these models.[20] This may partially be due to the preliminary nature of most models: when one is busy trying to show that the thing simply works at all one may be forgiven for not worrying what the average outcome of a hundred replications of the same model run might look like. It may also reflect a reluctance on the part of modelers to come to grips with the issue, given both the magnitude of the computational effort to generate a single model run and the complexity of the outcome of the simulation experiment -- i.e., a massively multi-dimensional data structure defining the final system state.

Come to grips with this issue, however, we must, for the output of any single run of a stochastic model is simply one random "draw" from the unknown distribution of possible outcomes. The representatives of this single outcome (and hence its usefulness for planning purposes) is also by definition unknown. In "classical" stochastic simulations, this problem is resolved by executing many replications of the run, each one of which generates additional information concerning the underlying unknown distribution of outcomes. This process continues until one has generated a sufficient number of observations to be able to say statistically meaningful things about the distribution of possible outcomes -- in particular to provide reliable estimates of the means and variances of the final system state.

Much work is required to address this issue in the case of activity-based travel demand microsimulation models. Considerable experimentation is needed to determine the statistical properties of both individual model components and of overall modeling systems — in particular to develop guidelines concerning when replications need to be undertaken and, if performed, how many are generally required. As Axhausen [1990] points out, many standard methods exist for reducing internal variation within simulation model runs, and the usefulness and appropriateness of using such methods must be investigated. Finally, thought must be given to how one does "average" over a set of simulated outcomes in cases of such complexity and high dimensionality as are typical of our applications.

5. Demonstration of computational feasibility. One should never make the mistake of underestimating the computational intensity of microsimulation models. In addition to requiring

[20] Axhausen [1990] is one of the few authors who spends more than a sentence or so on the issue. Many do not raise the issue at all.

considerable amounts of CPU time, the memory and disk storage requirements of a large microsimulation model are enormous. Early microsimulation models quickly bumped up against computational limits and/or made significant design comprises in order to maintain computational feasibility. With continuing rapid expansion of the computing power cost-effectively available to both researchers and planners, the definition of what is computationally feasible is being upgraded almost daily. Indeed, the fact that this paper is being presented at this conference is due almost entirely to the extraordinary computing power which is now routinely available to us (relative to even a few years ago), as well as to the universally held expectation that this trend of increasing computing power will continue into the foreseeable future.

Nevertheless, the computational challenges associated with large-scale microsimulations are significant, to say the least. This is particularly the case for population-based (as opposed to sample-based) models. The magnitude of the problem also grows as we move towards more integrated, comprehensive models (e.g., combined models of residential and employment location choice, activity/travel and network assignment).

Ultimately, all of the issues discussed above come together and interact with the issue of computational feasibility in a classic engineering design problem involving tradeoffs between "cost" and "performance". Every increase in model disaggregation, every extension of its comprehensiveness, every improvement in its statistical reliability comes at a cost in computer time, memory and storage. Conversely, at any point in time, current computational capabilities establish upper bounds in terms of what is cost-effectively doable within the model.

One can think of disaggregation level, extent of comprehensiveness, statistical reliability and computational requirements (among undoubtedly others) as fundamental attributes or dimensions of microsimulation model design. We have only become to explore the design "space" defined by these dimensions. At this point in time we have only the faintest notions of where feasible regions lie within this space, let alone where "optimal operating points" might be found.

Above all else, what is required is considerably more experience in building and using such models. The TRANSIMS project is providing invaluable experience in this regard, but we should not be counting on any one project to provide all the answers. The more experience which is gained by more people in more applications within more computing environments, the better our models will ultimately be — and the more likely it will be that we will end up developing the models which we actually need and can use. In any modeling application, a certain amount of "empirical wisdom" is required before the model can be reliably applied. Such empirical wisdom can only be achieved through doing: by trying, by failing, by experimenting, and, throughout the process by learning and thereby eventually (hopefully) succeeding.

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SUMMARY OF WORKSHOP ONE: ACTIVITY AND TIME USE DATA NEEDS, RESOURCES AND SURVEY METHODS

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Objectives

The workshop set out to address the three key questions posed by Peter Stopher in his opening address to the conference. In the context of the workshop these were interpreted as:

1. What elements of the activity-based perspective to data collection are both desirable and immediately available and what steps are needed to bring these elements into practice in the short term?

2. What are the potential areas of application of activity-based data collection methods over the next 2 to 5 years and what opportunities and constraints are likely to influence the evolution of practice within this time frame?

3. What steps are needed in terms of dissemination, training and research in order to promote the integration of activity-based methods into the mainstream of transportation analysis?

The workshop participants comprised practitioners at MPO, State and Federal level, consultants specialising in data collection, as well as those with a more general background in transportation modelling, academics and other researchers. Whilst the level of interest in activity-based methods was high, few practitioners had direct experience of applying these methods themselves and so understandings and expectations regarding the current status and future potential of the methods varied widely.

A particular difficulty surfaced in the opening session when it was discovered that a significant number of those present were unfamiliar with the fundamental differences between activity-based and trip-based survey instruments in current use. As the second session was on the succeeding day, it was possible, thanks to the quick action of several consultants and practitioners, to assemble and present a sample of recent instruments, which then served as examples in the remaining discussions.

General Issues

In addition to the broad issues raised by Peter Stopher, the contributions by the discussants Kay Axhausen and Ken Cervenka highlighted two further important issues that provided a backdrop to the deliberations of the workshop.

- The need to recognise that the complexity of the data which we would wish to collect and use is increasing (due to both new modelling requirements and the increased complexity of the policy environment). This raises important issues regarding assessing and improving the quality of data collection and about the optimal trade-off between quality and quantity in data collection.

- The need to recognise that the priorities and practices of transportation planning authorities vary greatly as do the resources and expertise available at the local level. New methods developed and training/dissemination activity undertaken should be sensitive to these variations. This means finding ways of facilitating some authorities in making a transition from 4-step to activity-based modelling whilst also providing mechanisms to support other authorities that currently undertake little or no formal modelling work in adopting the activity-based approach anew.

General Characteristics and Status of Current Activity-Based Data Collection Methods

Drawing on the diversity of background and experience of the participants, and the examples of instruments presented, the workshop attempted to clarify the characteristics and status of existing activity-based methods. The view was that activity-based data collection methods are defined as much by the use to which the data are put as by the method of collection *per se*. However, particularly in the case of travel demand data, the workshop was able to identify some broad characteristics that were felt to distinguish activity-based approaches. These included:

- A focus on the relationship between travel and the activities generating the demand for travel. This is a subtle but important difference. For example, whereas in a conventional (trip-based) approach a respondent might be asked to recall all the trips they made yesterday and the purpose of each trip, in an activity oriented approach they would be asked to recall the activities in which they participated and how they travelled between these activities.

- Developing naturally from the focus on activities, is a strong emphasis on issues of the sequencing and scheduling of behaviour. The activity based perspective emphasises the overall structure of activity/travel relations, both spatial *and* temporal.

- The emphasis on timing in turn leads to a concern with the dynamics of behaviour in terms of the relationship between different elements of behaviour within a day, the relationship of behaviour on different days and the effect of a wide range of changes in factors (socio-demographic, economic, technological or regulatory) on behaviour in the longer term.

- A final feature identified was an emphasis on household and institutional constraints as factors influencing travel behaviour. Just as trip making is viewed as part of a wider pattern of activity participation, so the behaviour of the individual is placed within the wider context of household decision making, taking account of the consequent inter-personal and institutional constraints placed upon freedom of action.

Elements of Activity-Based Models

In order to further explore data needs, Ken Kurani and John Polak laid out the main elements of activity-based models. These were summarised as:

- Activity generation/participation:
  - activity opportunities
  - time-use

- Activity scheduling:
  - timing, sequencing, duration
  - planning

- Activity execution:
  - network events
  - re-planning

- Dynamics:
  - within day
  - day-to-day
  - weekly
  - longer term

- Cognitive:
  - perceptions
  - learning

- Policy sensitivity:
  - information systems
  - pricing/tolling
  - regulation
  - non-transport measures
  - non-motorized transportation
  - land-use effects and impacts
  - in-home/out-of-home opportunities
  - derived analyses (environment, QOL...)
  - etc.

Specific Types of Activity-Oriented Data Collection Method

A number of different types of activity-oriented data collection method, relating both to demand and supply data were identified and discussed.

Demand Data

- *Activity diary surveys:* These are the activity-based counterpart of traditional travel diaries and are relevant to a similar range of modelling issues, principally the description of baseline population behaviour and the development of cross sectional models. They involve respondents reporting activities and travel rather than just travel and may also involve the collection of a limited amount of information regarding activities performed in the home. Experience suggests that activity diaries can be more effective at recovering mobility information than conventional trip diaries, especially information on short journeys and journeys made by non-motorised modes (which are often overlooked in trip diaries). A number of examples of activity/travel diary instruments have been used in the US in recent years and the benefits of the approach are beginning to be more widely (but by no means universally) accepted.

- *Panel surveys*: These are methods in which the same individuals are surveyed at two or more points in time, possibly, but not necessarily, by means of an activity diary. Panel surveys are principally of value in the assessment of impacts of new policies (before and after studies) and for the development of disaggregate dynamic models of travel demand (such as microsimulation models). The organisation and administration of a panel survey can be complex, but the data can be uniquely valuable, especially if the *turnover* of individuals who participate in different types of activity and travel has policy implications. A small number of panel surveys are currently in progress in the US, and there is more extensive experience of this method in some European countries.

- *Event-based surveys:* A variant of the panel survey and one that is especially suited to the investigation of long term demand issues is the event-based survey. In this approach respondents are tracked over a longer period of time, but rather than being surveyed at regular intervals (as is normally the case with panel surveys), then are only required to report key changes in circumstances as and when they occur (such as the acquisition or disposal of a car or a relocation of residence). Although experience with this type of survey is very limited, it was regarded as being potentially of considerable interest, especially in relation to modelling the relationship between demographic/land use change and mobility.

- *Stated Response surveys:* Most of these surveys, labelled "Stated Preference", involve presenting respondents with two or more hypothetical activity/travel situations and inviting the respondent to indicate which situation they would prefer or which they would choose. Some surveys on small samples involve more elaborate choice simulation exercises which are used to collect information on choice processes and the origins of choice-sets. The advantage of these approaches is that the researcher has control over the form of the hypothetical situations that are presented and therefore can explore new policy measures or complex behavioural processes that it would not be possible to address directly in the real world. Both these applications were regarded as being of considerable relevance to the development of activity-based models. The disadvantage of this approach is a concern over the validity of the results obtained and their transferability from a hypothetical context to the real world. Stated Response data is increasingly used by practitioners in the US, but some participants expressed concern about validity, transferability or even whether agencies who asked for such data really understood their limits.

However it was noted that for some types of issue, Stated Response may be the only feasible approach and that methods exist to enable the 'blending' of Stated Response and conventional Revealed Preference data, which can go some way towards addressing concerns over validity.

- *Passive data collection:* Developments in telecommunications and mobile computing are beginning to make it possible for certain types of behavioural travel data to be collected passively by means of remotely linked monitoring devices attached to vehicles and conceivably also to individuals. Accurate geocoding of trip ends and routes using Global Positioning Satellite systems, and real-time data transmission, are among the possibilities. Active research projects are currently underway in the US, Canada and Europe aimed at developing and testing appropriate systems.

Supply Data

- *Activity opportunities:* The main issue discussed in relation to supply data was how best to address the need that it was envisaged would arise (as a result of the development of highly detailed and disaggregate microsimulation models of travel demand) for much more detailed information on the spatial and temporal pattern of activity opportunities. This was seen as a major issue that can be only partially addressed through the enhancement of current digital databases. It was also regarded as raising difficult institutional issues concerning the relationship between the public and private sectors.

- *Network topology and performance:* In the same manner that detailed microscopic demand models were anticipated to give rise to new data requirements, so it was envisaged that the application of highly disaggregate traffic flow simulation models to larger and larger networks would give rise to a growing requirement for detailed and up-to-date network inventory data. Moreover, as both roadside and in-vehicle ITS systems are developed to play a larger role in some areas, so the scope of the inventory information required increases. Although this was not regarded as being as significant a problem as that posed by the activity opportunity data, a number of participants drew attention to the high costs associated with establishing and maintaining comprehensive network inventory data, and to the vulnerability of monitoring systems to funding cuts even where they have been established.

Progress Towards Consensus

The discussion revealed a tension between the preconceptions of practitioners and researchers. Understandably, many practitioners wanted a clear briefing on applicable and affordable new modelling and data collection techniques that would better equip them to deal with the increasingly complex policy issues. Perhaps equally understandably, researchers whilst quite clear about the benefits of activity-based approaches, preferred to emphasise the outstanding research issues and tasks.

Even though there was, in principle, more potential for consensus on the issue of data requirements and collection methods, we realised early in the workshop that there was little conventional wisdom on the strategies for selecting the optimal mix of data collection to feed the development of activity-based models. We need to draw particular attention to this insofar as there is a tendency to focus mostly on Revealed Preference data, notably activity-travel diary methods, to the exclusion of other data sources.

It was unfortunately not possible to arrive at a clear plan for the short (0-2 year) or medium (2-5 year) term horizons, or to address all the dissemination and training aspects of Peter Stopher's charge to workshops. However, we took a position on some important, concrete issues: (i) the most important data collection "unknowns and partly knowns" which deserved urgent research, development and innovation in order to bring activity-based data collection into practice, and (ii) some priorities for coordinating the process of activity-based travel forecasring implementation from the data perspective. These are briefly summarised below.

Priorities for Research and Development - the List of "Unknowns and Partly-knowns"

These issues were considered under two headings: the content of the information required and the techniques and methods appropriate to collecting such data.

Content

- *Information on in-home activities:* Current activity-travel diary methods at most provide only a very crude specification of in-home activities. Yet for a variety of reasons (e.g. growth of virtual environments, teleworking and other forms of flexible employment) the substitution/complementarity between in-home and out-of-home activities is likely to become an increasingly important issue. It is not clear how much detail it is necessary or feasible to seek on this topic.

- *Level of detail in activity-based surveys vs level of detail in activity-based models:* The emerging activity-based modelling tools are highly disaggregate and in principle make large demands in terms both of the description of population characteristics and understanding of behavioural response mechanisms. However, it is not necessarily the case that all dimensions of these data are required simultaneously. For example, the ability to synthesise populations from marginal distributions of population characteristics means that it may be possible to significantly reduce the data requirements for model application. This is one of a number of areas in which the workshop identified the need to establish close cooperation between model developers and data collection specialists.

- *Dealing with the long term:* Long term aspects of travel behaviour are not well understood and few existing datasets contain appropriate information. It would therefore seem desirable to focus new effort in this area.

- There was a recognition of an increasing need to understand how and why people make the travel choices they do, not simply what choices they make. That is, there is a felt need for better *"cognitive" as well as "behavioural" data.* Stated Response and related methods are one of the few ways of addressing this need. However, issues of validity and transferability must be seriously addressed.

- At a more practical level, we need to have a better understanding how to deal with *"non-forecastable" explanatory variables* within a forecasting context.

Techniques

- *Non-response*. Problems of non-response and incomplete response are already serious issues in conventional travel surveys. The scope for these problems to increase in magnitude as we move towards potentially more complex survey instruments is substantial. Moreover, a peculiar advantage of data collection around activity patterns is the inclusion of all traveller segments. In short, activity-based models face more *complex* non-response and response bias problems than do trip-based models. It therefore appears urgent to better understand both how to reduce the incidence of non-response and, given that it will nevertheless continue to occur, how best to detect it and to deal with the consequences. More work is needed on the merits and problems of such strategies as the use of aide-memoires in telephone surveys, re-contacting respondents, rostering between responses from members of the same household, imputation, etc. Also, the workshop recognised growing support for an more "open", detailed reporting of non-response and incomplete response for different *subgroups* of interest. This implies that an adequate set of descriptors of both respondents and non-respondents is recorded, and it was noted that these may not be the same variables or classes which are required for the analysis of survey results.

- *Event-based methods to reduce respondent burden:* One aspect of attempting to reduce the problems of non-response is reducing respondent burden, and in this connection it was consider potentially worthwhile to investigate further the scope for "event-based" reporting strategies within behavioural surveys, especially those addressing longer term issues.

- *Integrated data strategies*. It is clear that no single data collection method is capable to furnishing all the required information. Rather, there is a need to integrate data from different sources. Techniques for approaching the problem of merging data from a diverse collection of sources are available, but are generally not well known within the transport research community. Further work in this area would therefore seem justified.

- *Talking the respondent's language.* Limited research has been undertaken into how respondents understand (or otherwise) the concepts that are presented to them in typical travel behaviour surveys. Elements of survey grammar are often driven by the grammar of a model. However, this may not be the most effective means of extracting sound data. Therefore research into respondents' comprehension and understanding of typical survey grammars would appear desirable. The ethics of passive data collection must also be addressed, although it was recognised that the problems in this area may have been exaggerated, and that the work most needed is on the institutional aspects of responsible data management (e.g. for the production of transparently anonymous disaggregate data files) and on the field testing of appropriate ways of obtaining informed consent.

- *The role of Stated Response methods.* These methods appear in principle to have a major role to play in the development of the behavioural response models that will be embedded in microsimulations of travel demand. There was felt to be a need to clarify the role of such techniques and in particular, as pointed out above, to seriously address the issues of validity and transferability.

- *Exploiting technology:* Technologies are advancing rapidly and this opens up new opportunities for the collection and collation of data. The potential for individual passive monitoring has already been discussed and it would seem highly desirable to reinforce the existing research initiatives in this area. There is also important progress that could be made in terms of the secondary use of aggregate data sources such traffic monitoring system and automatic tolling systems.

Implementation Issues

The workshop identified three broad strategies that it believed would be of value in advancing the dissemination and implementation of activity-based methods.

- *Cooperation* between research into model development and research into data collection methodology. The need for research in these two areas to proceed jointly was regarded as being of paramount importance.

- *Test Bed:* The facilitate the co-development of modelling and data methods, the idea was put forward of "integrated sites" with unusual attention paid to the collection of both demand and supply data. Such integrated sites could act as test beds for the emerging data and modelling developments.

- *Justification:* Practitioners need both a rationale for shifting to from 4-Step to Activity-Based Travel Forecasting and a straightforward explanation of the differences in forecasts likely to be produced by the two types of model. The workshop noted that these should focus on the anticipated superior performance of activity-based approaches in estimating the effects of *simultaneous changes* in both the population and the supply characteristics. Ideally, more effort should be made to run both types of model in parallel in a small number of test cases, thus allowing planning agencies to weigh an increased amount of "real" evidence.

Other Issues Identified As Important

At the end of the workshop, participants also identified three areas as meriting discussion, but which did not get covered sufficiently in the time available to become the subject of recommendations:

- *More on uses of secondary or "support" data sources:* In addition to aggregate sources from transport systems (such as traffic monitoring system and automatic tolling systems, mentioned above), the workshop would have liked to examine the potential roles of such external sources as electronic directories to improve geocoding, or credit-card transaction databases.

- *The secondary analysis* of important existing travel data, as well as its "intelligent archiving" (meaning that the accumulated knowledge about the performance of data is preserved in a database system, together with the database itself).

- *Planning area boundaries:* How extensive an area should be covered by activity-based data collection and the model which it feeds? Are MPO boundaries the only realistic definition of the appropriate universe?

Summary of Workshop Two: Models of Activity Engagement and Travel Behavior

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INTRODUCTION

This workshop primarily focused on the availability, use, and research needs of activity-based models of travel behavior. The workshop group consisted of academics, consultants, practitioners from public agencies, and researchers providing a forum for the brisk and informative exchange of diverse viewpoints and perspectives. The workshop convened over a two-day period with specific objectives charged to the group in order to ensure that a clear set of recommendations emerged from the discussions. The workshop started with presentations by two discussants who offered their perspectives on activity based models of travel behavior. Following their presentations, the group worked on developing an ambitious agenda for moving activity-based models of travel behavior into mainstream practice.

PRESENTATIONS BY DISCUSSANTS

Chuck Purvis, with the San Francisco Bay Area MTC, served as the first discussant for the workshop. His presentation served as an opening practitioner perspective on the topic of activity-based modeling and his thoughts were echoed repeatedly by members of the group over the two-day period. Chuck mentioned that models need to respond to different scales of analysis including regional and subregional modeling efforts that MPO's typically engage in on a day-to-day basis. Models need to be especially responsive to network-level issues which are the primary concern of transportation planning agencies. Rarely do the MPO's concern themselves with new transport policies such as congestion pricing, parking surcharges, and other transportation control measures (TCM).

Chuck also mentioned that models should be understandable to practitioners. He indicated that, for most MPO staff persons engaged in travel demand forecasting, techniques such as structural equations, neural networks, and hazard functions of survival models are complicated. There is a need for training to understand and apply these procedures. In addition, he felt that there is a clear need for proving the performance of new modeling methods before they are accepted and implemented in practice.

Tom Golob, with the Institute of Transportation Studies at the University of California, Irvine, served as the second workshop discussant. Tom presented a structural equation model system that models the two-way interactive relationships between activity engagement behavior and travel behavior. In developing the model system, several aspects of travel and activity behavior were addressed. Interactions between household members were taken into consideration. Tom noted that there may be activities that household members engage in as a group and that cars owned by a household have to be shared by all driving members. The trade-offs involved when considering in-home activity engagement as opposed to out-of-home activity engagement also were addressed. Tom also addressed the degree of flexibility associated with various activities. He classified various activities into three broad categories, namely, work and work-related, maintenance (shopping, personal business, etc.) and discretionary (social recreation, etc.). Mobility may be represented by trip rates by mode, travel times, and travel distances (vehicle miles traveled). The structural equation system was estimated on data from Portland, Oregon to relate activity and travel behavior to a set of exogenous or explanatory variables. Tom noted that the model system can be extended to consider such aspects of behavior as trip chaining, ridesharing (driver or passenger), and use of non-motorized modes for short trips. In addition, Tom indicated that stated preference questions can also be incorporated into the model system thus providing a more powerful TDM policy analysis tool.

Various issues were raised in light of Tom's presentation. Some of the issues raised included the following:

- Analysis of weekend activity behavior and travel
- Use of longitudinal data to track changes in behavior over time
- Stability of relationships over time; it was noted that relationships are more likely to be stable in the short-term as opposed to the long-term
- Day-to-day variability in activity and travel behavior
- Need for supply side models; how does travel time and distance relate to congestion levels on network

Following the presentations by discussants, the group addressed four fundamental questions with regard to models of activity engagement and travel behavior. They are:

1. What activity-based models or techniques are available to use now?
2. What needs to be done to bring these models into practice within the next two years?
3. What are the application areas where activity based models may be applied in the next five years?
4. What are the barriers to implementation and what needs to be done to overcome them to facilitate moving activity based models into mainstream practice?

QUESTION 1: MODELS IMPLEMENTED AND/OR AVAILABLE

The group discussed several model systems that have been implemented or are available, but have not been implemented yet in a real world environment. The group felt that there are several categories into which model systems may be classified depending on their level of complexity and the extent to which they replace or interface with various components of the currently used four-step UTPS process.

With regard to models that have been implemented and tested in a real-world environment, the workshop group identified several model systems. First, the group identified models that constitute an extension of the current UTPS process where elements of activity based analysis are incorporated into current modeling procedures. The effort at the San Francisco Bay Area MTC was mentioned in this regard.

A second class of model systems involved the use of discrete choice methods to model the choice of activities and/or trip chains that people pursue. In this context, three model systems were identified by the group. These included the Dutch National Model, the Simulation Model System (SIMS) applied in Stockholm, and the discrete choice models implemented in Boise, Idaho and New Hampshire.

A third class of models was considered to offer a higher level of complexity and detail with regard to the modeling of activity and travel patterns. This class involved the microsimulation model systems of AMOS (activity mobility simulator) tested in the Washington D.C. metropolitan area and MIDAS (microanalytic integrated demographic accounting system) that was tested in The Netherlands.

The typology of models implemented may be summarized as follows:

- Extensions of UTPS Process
  - San Francisco Bay Area MTC

- Discrete choice models
  - Dutch National Model
  - SIMS (Stockholm)
  - Boise, Idaho
  - New Hampshire

- Microsimulation models
  - AMOS
  - MIDAS

In addition, the workshop group identified a few other model systems that have been developed, but have not yet been implemented in practice. One of the model systems is the Activity Tour Model developed at MIT and being implemented in Portland, Oregon over the next one to two years. Another model is TAMOS (transactions activity mobility simulator) that is being developed for the California Energy Commission. Also mentioned were STEPS, a model system developed in Berkeley, California, and a series of models that have been developed in Europe, but have not yet been implemented in practice. These mainly include activity scheduling models such as CARLA, SCHEDULER, SMASH, and DynaMIT. The workshop group made a note that very little is known among practitioners about international efforts and that there is a greater need for the dissemination of model development news.

Several issues were raised regarding the availability and implementation of model systems that have been developed over the last several years. These include:

- The definition of a tour or trip chain for activity based modeling of travel behavior. Several different definitions have been used across model systems and the need for a consistent definition was felt.

- There may be two avenues that are necessary for the implementation of activity based models; one avenue involving the upgrading of existing elements of UTPS and another involving an overall upgrade to a new model system.

- The diversity of methods is mind-boggling for the practitioner. There is a need for a greater amount of consistency of procedures.

- The question was raised as to whether models that have been successful in one location can be applied in another location? Do activity based models have the same difficulties in transferability that trip based models have?

QUESTION 2: STEPS FOR IMMEDIATE IMPLEMENTATION

The next question addressed by the workshop group was concerned with the steps that need to be taken to move the existing models (identified in Question 1) into practice within a very short time frame. A very lively discussion raised and addressed several issues concerned with immediate implementation of activity based model systems.

The group felt strongly that the applicability of activity-based models needs to be demonstrated in practice in an environment that is either their own or very similar to their own. The workshop strongly recommended that demonstration projects be conducted in several areas across the country. The areas should be of a diverse nature with considerable variation with respect to the following characteristics:

- Size (large, medium, and small)
- Population density
- Intensity of development
- Strength of CBD
- Urban vs. rural characteristics
- Availability of activity vs. trip-based data

In addition, the demonstration projects should involve the testing of multiple methods to facilitate a comparison of various methods and a determination of the methods most suitable for different planning environments. The group indicated that implementation will occur only after a proof of concept has taken place in the real-world.

Another major thrust area identified by the group was the formation of partnerships. It was felt that academics, researchers, MPO's, and consultants need to work together to make activity based modeling a reality. MPO's would like to understand the tool and its capabilities thoroughly before they actually use the model systems for their planning studies. It was felt that partnerships among the various developmental and user groups would greatly accelerate the movement of these methods into practice.

MPO's and practitioners indicated that they were not aware of how close and suitable the various models were to actual application in practice. They indicated that MPO's need models that can applied immediately as they do not have the time and resources to develop new model systems or customize generic model systems to their environment. Also, the group noted that MPO's need to make a slow transition from their current modeling procedures to the new modeling procedures. In fact, for some time period, it is anticipated that parallel procedures will be in place until an MPO is willing to completely adopt a new modeling method. Also, MPO's are of a very diverse nature. While some MPO's may have the technical abilities and staff resources, they may not have the data needed for implementing the models. At other MPO's, the reverse may be true. As such, there is a need to customize activity based modeling procedures to the specific situation in which they will be applied.

Education, training, and information dissemination through workshops, reports, short courses, and seminars were identified as key ingredients to the process of moving activity based methods to practice. It was felt that TMIP should take a lead in these efforts to keep practitioners fully informed of activity based model developments. In addition, it was felt that the technical and policy staff at planning agencies would have to be trained and educated about the new modeling methods before they can be applied in practice. Universities and industry should take a lead in offering short-courses, on-site training, and do-it-yourself user manuals for the application of activity based models.

Several other issues were raised in regard to the immediate application of activity based models in practice. With regard to the question of why MPO's have been slow in adopting new procedures, it was felt that time and resources (staff and funds) were too scarce to allow radical changes. Federal support is needed to facilitate the transition to new methods. It was felt that other planning agencies such as land use planning boards, city and county transportation divisions, and other agencies that are affected by transportation planning decisions should also be involved in any transition to new modeling methods. It must be ensured that activity based models are responsive to local, state, and federal legislative requirements as they govern and dictate many provisions of the planning process.

Some concern was raised with regard to a comparison of existing modeling procedures with activity based models. If the modeling processes offer different results, then how does one know which is correct? The group felt that activity based models should be able to replicate base year conditions and be responsive to new transport policies without having to apply various adjustment factors that are often applied in UTPS models. Also, it was felt that the results obtained from activity based models would, in many instances, complement and not compete with those provided by traditional UTPS models.

QUESTION 3: APPLICATION AREAS FOR FIVE YEAR IMPLEMENTATION

The workshop group discussed the various types of application areas for which activity-based models may be applied in a few years. The group discussed several issues in light of the different planning needs of transportation agencies. One issue dealt with the potential difficulty of relating activity-based information to network flows that most transportation planning studies typically need. The potential for activity based modeling to address land use impacts of transportation decisions in a more robust framework was identified as a key advantage of activity based analysis. The need to model trip making on a point-to-point basis rather than a zone-to-zone basis was mentioned as another area where activity based models may offer unique capabilities. GIS databases and procedures may offer powerful tools in this regard. The group felt that destination choice is a key challenge facing travel behavior modelers at the present time. In order to demonstrate that activity based models can be used for planning studies, one member indicated that activity based models should be applied in an urban context where only traditional zonal trip data are available as only a very few urban areas around the country are collecting detailed activity data.

The group identified three classes of application areas in which activity based models may be applied over the next few years. These are briefly discussed below:

Traditional Planning Studies

The group indicated that MPO's typically spend most of their time doing traditional planning studies and that activity based models would have to lend themselves to these types of applications to be accepted in practice. Examples of these studies included:

- Long Range Transportation Plans
- TIP Conformity Analysis
- Land Use Impact Analysis
- Project Development and Evaluation

Policy Questions

A second application area identified by the group pertained to the analysis of new transport policies. The group felt that this is the area where activity based models hold the greatest promise as traditional UTPS type modeling procedures were not developed to handle policy questions related to the implementation of travel demand management strategies, transportation control measures, and new technologies. Examples of policy questions identified by the group included:

- Congestion pricing
- Employer trip reduction programs
- Intelligent Transportation Systems

- HOV and Car/Vanpool programs
- Fare structure changes and tolls
- Other TDM strategies and TCM's
- Alternative fuels

Non-Traditional and Other Studies

Finally, the group identified a third class of planning studies which is intended to serve as the "catch-all" category for those that don't fall into the previous two categories. Within this category, the group identified special planning studies that deal with the study of unique population segments or rare behavior. Examples of special studies that could be included in this class were identified as:

- Analysis of special population segments (elderly, handicapped, etc.)
- Equity studies of transportation investments
- Analysis of Non-motorized mode use
- Telecommunications impacts on travel

The group also noted that the movement of freight and the explicit recognition of intermodalism have been lacking in activity-based analysis and urged the research community to consider these aspects of the transportation system in future developmental work.

QUESTION 4: OVERCOMING BARRIERS TO IMPLEMENTATION IN PRACTICE

The final question addressed by the group was concerned with identifying the barriers to implementing activity-based models in practice and the steps that need to be taken to overcome the barriers. Some of the discussion related to this question overlapped with the discussion surrounding Question 2 where steps needed for immediate implementation were identified.

The biggest barrier to implementation in practice was identified as the lack of proof that activity based models would work in several urban contexts. The group emphasized that planning agencies around the country would not adopt activity based models in mainstream practice until they are convinced of the credibility of such models and are confident of the results they provide. In order to establish credibility and confidence, the group identified two preliminary criteria that may be of use to researchers and developers:

- Activity based models should be able to replicate base year conditions without having to apply various adjustment factors that are typically used in UTPS modeling procedures

- Activity based models should be sensitive to new transport policies (such as TDM strategies and TCM's) that current UTPS models are not equipped to address and should provide intuitively meaningful results

In this regard, the group once again strongly emphasized the need for a multi-location demonstration study where multiple activity based methods would be applied in different types of urban contexts to prove the abilities of activity based models in meeting planning needs.

Another major barrier to implementation was related to data requirements for activity based modeling and the monetary resources needed to collect such data. The group felt that it would be prudent to study the transferability of activity based data. In this regard, it was mentioned that the variability in activity engagement rates is much smaller than that for trip rates, perhaps making activity data more transferable than traditional trip data. Within this context, the group noted that funds should be made available to local planning agencies to consider implementation of activity based models. As implementation of new model systems is resource intensive and local planning agencies are already operating under tight fiscal constraints, it was strongly felt that MPO's would be very slow to consider new modeling procedures without monetary assistance from the federal agencies.

Staff expertise and training needs were identified as another major requirement for moving these methods into mainstream practice. The group mentioned that various technology transfer and training materials should be made available for planning agency staff to become knowledgeable in the area of activity based analysis. Primers or readers on activity based models, short-courses, conferences and workshops, demonstration studies with researcher/practitioner partnerships, and on-site software training were identified as the main ingredients to effective technology transfer.

In this context, the group also talked about short-term research needs to address some of the issues in activity based analysis for which adequate insights have not been obtained. The research needs identified include:

- The impacts of land use patterns and destination opportunities on activity patterns need to be determined and the underlying relationships should be unraveled using real-world activity data that is merged with land use data

- The level of detail needed from models for various types of planning applications should be determined in order to identify the types of modeling methods most appropriate for different applications

- Detailed descriptions of activity patterns and how they relate to travel patterns are needed to establish the link between activity information and travel on networks

- Transferability of activity data should be studied in light of the fact that only a very few urban areas have collected detailed activity data

- A synthesis of time use surveys should be undertaken to summarize the lessons learnt and knowledge gained from such surveys

Finally, the group indicated that while these short-term research needs will provide benefits for moving activity based models into practice, it should be recognized that activity based models are the culmination of decades of research into travel behavior and its underlying forces. As such, the value of long-term research should be recognized and long-term research and development efforts should be continued to further enhance model specifications and estimation methods.

In summary, the steps that would help move activity based methods into mainstream practice are as follows:

- Multi-location multi-method demonstration projects to prove concept in practice
- Researcher/practitioner partnerships
- Education and training
- Reader/Primer on activity based methods
- Conferences, workshops, and short-courses around the country
- Monetary resources and incentives
- Sample activity data sets with computer model demos
- Continued support for long-term research and development

The workshop group concluded its discussions at the end of the second day having accomplished its mission.

SUMMARY OF WORKSHOP THREE: MICROSIMULATION IN ACTIVITY ANALYSIS

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The Activity Based Travel Forecasting Conference was designed to allow practitioners, researchers and the academic community to discuss and formulate a general consensus on the following three objectives.

1. What applications are ready for use, what are they and what is needed to make them functional in the planning community.

2. Define the application areas not readily available, research require to develop functional models, and determine how to move them into practice

3. How to disseminate the application areas, encourage use of new methods, provide adequate training and continue research.

Micro-simulation:

The micro-simulation workgroup participants represented a diverse mix of public and private practitioners and the academic/research community. As the workgroup session began to unfold, it was obvious that many of the practitioners in the group had very limited experience in using microsimulation techniques or tools in their daily planning activities. Generally, most were aware of some type of *network* micro-simulation application, but few had experience using more complex land use and transportation demand simulation models. The academic and research participants presented to the group a review of the current research activities and potentially viable techniques available for implementation.

As discussion continued, it was further evident that many did not adequately understand the types of inputs required for micro-simulation models nor the type of analytical techniques required in interpreting the output of the models. In fact, during a somewhat intense exchange of confusion, it was pointed out, that as with any modeling (sequential or micro-simulation), one must still think about and analyze the output.

It was concluded from the discussion that traditional analytical tools would not be enough or even adequate to analyze the new databases created within the micro-simulation modeling process and new techniques would have to be taught to practitioners. Also emerging from the discussion was the awareness that as new researchers and practitioners enter into the field of transportation and land use planning, they may in fact be required to learn two sets of tools to use in real world applications.

Workshop Summary

Based on the objectives of the Conference and the discussions within the workgroup, it was agreed that the summary of the work group sessions focus on the following four areas:

1. Applications: What tools are currently available for microsimulation?

2. Obstacles: What stands in the way of implementing the tools?

3. Mechanisms: How can the planning community incorporate the new techniques into their current planning paradigms?

4. Research: What are the application issues and policy implications, what type of models and processes are needed, and what would the methodological framework of the new models be?

Current Applications

Discussions focused on what applications have been used or are currently being tested in real world cases.

- A few of the larger Metropolitan Planning Organizations have used the "STEP" software to carry out household-level "micro-simulation" of travel, in Boise, Idaho, a Tour Base Model has been developed, and there has been some work using the disaggregation of traditional production and attractions matrices.

- The Los Alamos effort and others have demonstrated the feasibility of the micro-simulation of population. Employment location/simulation modeling has not been addressed adequately.

- Researchers and private practitioners have used many of the network simulation models, those mention included Dynasmart, and Integration. Neither simulation package has multi-modal capabilities.

- The dynamic micro-simulator Activity-Mobility Simulator (AMOS) is being tested as a prototype for analyzing Travel Demand Management (TDM) policies in the Washington D.C. area.

- Also discussed was the new data technology changes and how they fit into the scheme of collecting data. The electronic directory of land use activity (firm location) and its potential tie-in with spatial data software (GIS) were mentioned.

Obstacles

The workgroup next focused on what were the key obstacles in preventing a smooth transition to using micro-simulation tools in the planning practice.

- Change. Institutional fear and/or the lack of in-house technical expertise were considered the primary obstacles in incorporating new techniques in the current planning paradigm.

- Level of training and (re-) education needed for new technologies and methodologies initially are staggering. With no clear direction established, it is very difficult to invest monies and staff time at the current time.

- Distinguishing how the new techniques fit with current modeling methodology and how does one compare them was a key point brought up by the workgroup. Concern was raised on how does one directly compare outputs from uniquely different approaches. Will it be an apples to apples comparison or will we need to be addressing similar questions with different approaches.

- Developing as a theme for the Conference was a "Show Me that it really works mentality". Though a lot of theoretical and some hands on methods were described, no tangible tools or methodologies could be agreed upon. Very few practitioners envisioned changing their current planning processes in the near future.

MECHANISMS

The workgroup next examined the potential mechanisms that would be required to begin the process of incorporating activity-based micro-simulation in today's planning environment. Though not inclusive the following were the top five suggestions developed by the workgroup.

- First and foremost it is essential that we need to take an *incremental approach* in implementing the potential new planning tools. This incremental approach should incorporate both the transition to new analytical tools and the training required to use them.

- *Good* documentation of new techniques, showing when and where they are applicable in the planning process is imperative. One needs to understand the benefits and the short-comings of using the new tools over current tools and practices. Developing interactive tutorials or class room courses were a few of the examples discussed by the group.

- If practitioners are to change the tools and processes used to meet Federal (and State) requirements, acknowledgment of the difficulties inherent in the transitioning process must be developed. A Federal or State decree on the issue must be established as well as a concerted effort to provide guidance to the many players in the planning and research professions.

- The regulatory environment *must* be supportive of the changes required in transitioning to new methodologies. In particular, concern over interpretation of air quality findings between two different modeling methodologies and the implication on conformity, Federal and State environmental regulations, and potentially, traffic mitigation issues.

- It was also suggested that the technical community ride the wave of emerging technologies to obtain key data required for new modeling paradigms and validation of outputs. This includes the myriad of Intelligent Transportation System (ITS) components (e.g., Automated Traffic Information System (ATIS), Automatic Vehicle Identifier and Location (AVI/AVL), etc.).

RESEARCH NEEDS

The last area of discussion by the workgroup was research required to assist in the implementation of micro-simulation into the planning arena. Many ideas were presented and they have been categorized into three parts, application and policy issues, models and process, and methodological framework. To adequately address the research needs and optimize the potential for implementation, equitable resources should be focused on all of the areas.

Application and Policy Issues

Many application and policy issues were discussed and narrowed to the following:

1. What level of representation is required to obtain reasonable and defendable results?

2. Understanding of the uncertainty inherent within the process. How can the analyst "bracket" the uncertainty.

3. Determining the role and type of modeling approach for specific policy questions will need to be addressed.

4. Establishing an evaluation framework for potentially many different modeling approaches should be done before many of the new tools are implemented.

Models and Process

Expressed by the group was a need have a broader based approach on model development. It was felt that current emphasis still seemed to be primarily focused on traffic simulation. Other topics for further research included;

- Modeling demand sensitivity to changes. The changes can be in the form of new information technologies or an actual physical change in the transportation supply.

- Research on the modeling of multi-modal interactions, including non-motorized and freight and goods travel, on both the supply and demand side should be furthered.

- Urban activity micro-simulation should be enhanced. In particular the gap between the ability to simulate population and the seemingly lack of attention to employment must be narrowed.

- Continue model development in the area of activity schedules/plan generation. Examples include tour based modeling and trip chaining.

Methodological Framework

Discussions on the framework(s) in which the new applications are to be used generated a lot of debate. The following summarizes the groups priorities for further research and direction.

- How will the new techniques handle different time and spatial scales?

- How will decision hierarchies be incorporated into the new methodologies?

- How will the output developed from the models be used and what are the representation and modeling implications?

- How does one interpret the propagation of variance, error, etc.. Within the new modeling methodologies.

- What are the minimum entity representations required within the new framework?

- What techniques need to be developed to accurately assess the models performance?

- How do we address the output/storage challenges inherent in such a data intensive system?

- How can the new models be designed to insure that there would be maximum computational performance?

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