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The sequenced activity mobility simulator (SAMS): an integrated approach to modeling transportation, land use and air quality

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Abstract. The persistence of environmental problems in urban areas and the prospect of increasing congestion have precipitated a variety of new policies in the USA, with concomitant analytical and modeling requirements for transportation planning. This paper introduces the Sequenced Activity-Mobility Simulator (SAMS), a dynamic and integrated microsimulation forecasting system for transportation, land use and air quality, designed to overcome the deficiencies of conventional four-step travel demand forecasting systems. The proposed SAMS framework represents a departure from many of the conventional paradigms in travel demand forecasting. In particular, it aims at replicating the adaptative dynamics underlying transportation phenomena; explicitly incorporates the time-of-day dimension; represents human behavior based on the satisficing, as opposed to optimizing, principle; and endogenously forecasts socio-demographic, land use, vehicle fleet mix, and other variables that have traditionally been projected externally to be input into the forecasting process.

Introduction

The Sequenced Activity-Mobility Simulator (SAMS), the microsimulation model system described in this paper, is envisioned as an effective planning and policy tool that is capable of addressing many of the current critical issues which conventional approaches have not been able to address.[1] The contexts in which this model system originated, the needs for a new model system, and the reasons why the conventional models are unable to meet these needs, are discussed in this section.

Contexts

The Clean Air Act Amendments (CAAA) of 1990 renewed the United States' commitment to air quality by focusing on efforts to reduce episodic exceedences of the National Ambient Air Quality Standards, as well as by setting specific time-paths for their achievement in different regions according to the severity of their ozone and carbon monoxide violations. While technical improvements have been made in cleaner fuels and vehicles, estimates indicate they will be insufficient in meeting CAAA emissions reduction requirements. Continued VMT growth of 2% per year between 1990 and 2010 is expected to outweigh the benefits of a cleaner fleet, leaving a shortfall of approximately half of the CAAA-required emissions reductions in that time frame (Kessler & Schroeer, 1995). In addition, the effects of reduced emissions rates in newer model vehicles may be excluded from emissions reductions accounting.

Moreover, the CAAA expects travel demand management (TDM) to play an increasing role in addressing this shortfall between mandated emissions reductions and that brought about by anticipated technological improvements. The air quality conformity requirements for infrastructure investment demand analytical methods to evaluate the effects of added capacity on induced demand. A thorough treatment of travel behavior, a complex phenomenon involving the trade-offs and decision-making that people make in a variety of travel environments, is required to assess the impacts of TDM measures and capacity-related changes on mobility patterns, air quality, and land use.

Further, the 1990 CAAA specifically focuses on preventing episodes when the national ambient air quality standards are violated. In order to identify these episodes transportation models need to be able to estimate emissions that may occur at specific times during the day or year when congestion is peaking and temperatures are high, as well as for particular patterns of travel (say, holiday or weekend travel). Vehicle ownership models will have to forecast fleet rejuvenation by vehicle type and vintage in order to estimate whether emissions reductions targets will be achieved within the time frame specified in the CAAA, as well as to address the market penetration targets for low emission vehicles, ultra-low emissions vehicles and zero emissions vehicles.

In addition to the renewed interest in the link between transportation and air quality, there are other factors that mandate the development of new transportation modeling capabilities. These factors include socio-demographic changes (e.g., the aging of the population, the continued entry of women into the work force, changes in household structure) and technological advances (e.g., new information delivery systems, the incorporation of advanced communication systems in transportation system operation and management (Lee-Gosselin & Pas, 1995).

Needs

This increasingly restrictive and complex situation demands a far more comprehensive and integrated approach to transportation and land-use systems. Policy analysts will require transportation forecasting systems that can measure the cost-effectiveness and political feasibility (e.g., equity and distributional impacts) of a host of policy measures (singly or in combination) including: policies oriented toward transportation networks (e.g., level of service, capacity measures), toward travel behavior (e.g., market-based and command-and-control demand management measures), toward vehicle production and demand (e.g., CAFE, registration taxes, sales taxes, quotas), and toward land use (e.g., growth management, pedestrian- and transit-oriented neighborhood design).

The current and emerging policy and planning environment results in stringent analytical requirements to be met by the next generation of transportation model systems. For example, in order to predict travelers' short-term responses to TDM schemes, the model systems will need to be able to deal with a range of possible responses, including changes in the time-of-day and day-of-week of travel, number of trips, mode, destination, trip chaining, and substitution between in-home and out-of-home activities. Accurate representation of travelers' responses will require a higher degree of spatio-temporal resolution in the transportation model. The new model systems will also need to be able to endogenously represent the effects of changes in the vehicle market on vehicle purchases, retention and disposal, as well as on vehicle utilization. Further, the new model system needs to be sensitive to the fact that traveler responses to slow and cumulative changes (e.g., changes resulting from a gradual build-up of congestion) will differ from the response to sudden changes arising from the implementation of a policy measure. Finally, attention must be directed to the fact that the most fundamental determinants of passenger travel and freight transportation demand have been treated as exogenous inputs to the transportation demand forecasting procedure. These determinants – household structure, land use development and regional economy – are results of the socio-demographic evolution of households, their location and employment choices as well as the birth, growth and death of firms and their location decisions. These processes should be modeled endogenously in the new model systems if maintaining internal consistency of forecasts is desired.

Limitations of the conventional approaches

The limitations of the conventional four-step travel demand forecasting procedures have received renewed attention recently in the new policy and planning contexts set forth in the United States by the CAAA and ISTEA. Many of these deficiencies have been known for some time now; in fact Pas (1990) argues that the existing model systems are fundamentally the same as those introduced nearly 40 years ago with the exception that disaggregate models have replaced the original aggregate models. However, the recent legislation and the landmark lawsuit, brought by the Sierra Club Legal Defense Fund and Citizens for a Better Environment against the Metropolitan Transportation Commission (MTC) in the San Francisco Bay Area and the State of California, have made the need for a new framework more crucial.

A number of critiques have recently re-examined in detail the deficiencies of the conventional forecasting approaches (Harvey & Deakin, 1993; Stopher, 1993; Replogle, 1993; Kitamura et al., 1993). This brief overview focuses on the most critical deficiencies of the four-step procedures which arise because of the following two properties they commonly share: that they are formulated using the trip as the basic unit of analysis (consequently the discussions here also apply to many applications of disaggregate choice models that also tend to be trip-based), and that they lack the time-of-day dimension.

Trip based. The four-step procedures are specified with the trip as the unit of analysis; the series of trips made by an individual are treated as separate, independent entities in the analysis. Consequently the trip-based, sequential structure is unable to appropriately reflect the fact that the decisions associated with a particular trip are integrally related with the decisions for other trips. Furthermore, the recursive formulation posits trip generation as a decision made in isolation from the "trip's" potential attributes (and is therefore insensitive to congestion and pricing). The resulting model structure cannot fully capture the adaptive dynamics in traveler's responses to changes in transportation supply characteristics, and cannot address issues associated with induced and suppressed demand. Another example of the shortcomings of this recursive formulation is the lack of recognition that the trips made by an individual over a span of time (say, a day) are spatially connected and temporally sequenced and that the mode taken in the morning constitutes a condition of travel later in the day, or that the mode taken in the morning is dependent on planned activities later in the day.

Lack of the time-of-day dimension. Another important deficiency of the conventional travel forecasting model systems is that it lacks the time-of-day dimension. This is rather surprising considering that congestion, which arises from the concentration of traffic over *time* and space, is the major factor that has motivated transportation planning studies. This deficiency implies that these model systems are unable to predict changes in when trips will be made. This is a critical shortcoming in the current policy environment in which there is considerable interest in the implementation of congestion pricing schemes.

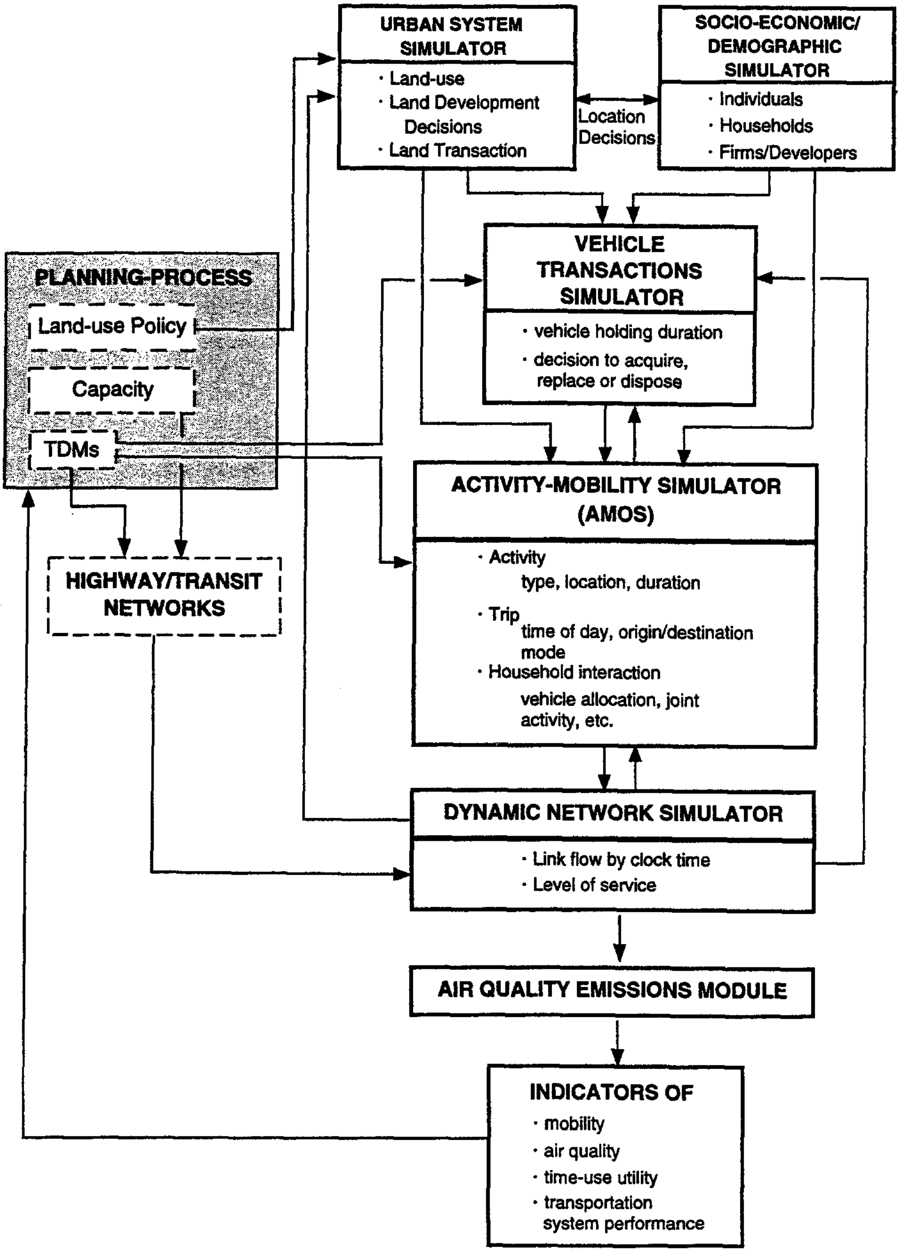
Other limitations of the conventional framework include the use of static models based on cross-sectional data, an inability to address the evolution of the vehicle fleet mix, and the use of exogenous land-use and socio-demographic inputs. These deficiencies severely limit the usefulness of the four-step procedures in much needed applications such as the evaluation of TDM effectiveness and the air quality conformity of capacity increases, and in meeting the other requirements identified earlier. Clearly, substantially new approaches are called for in travel demand forecasting.

Overview of the paper

This paper offers an overview of the Sequenced Activity-Mobility Simulator (SAMS) which is envisaged as the next generation urban transportation demand forecasting system which attempts to overcome the deficiencies of the existing forecasting systems. In the next section, SAMS is described while focusing on the paradigm shifts embodied in this new approach to travel demand forecasting. A brief description of the primary features of the SAMS model components is also provided. The discussions of the third section center on the key component of the SAMS model system, the Activity-Mobility Simulator (AMOS). In the final section, the data needs of the new modeling framework are described and issues associated with the development and implementation of SAMS are discussed.

SAMS: A new approach to transportation, land-use and air quality modeling

SAMS has been conceived as a policy tool that satisfies the analytical requirements that have emerged in the new planning contexts discussed above. It is envisioned as a comprehensive, integrated dynamic microsimulation model system that fully represents the interaction between transportation and land use; internally models the evolution of households and firms and their location behavior; predicts regional vehicle fleet turnover; and depicts the build-up and dissipation of traffic congestion through network simulation performed along a continuous time-of-day axis (see Figure 1 for an overview illustration). SAMS thus conceived, yet only partially implemented, endogenously forecasts socio-demographic change, land use development, vehicle holdings, as well as travel demand, network performance, and air quality. Below, the paradigm shifts embodied in SAMS are summarized, then a brief introduction to each of the SAMS model components is presented.



* The diagram does not incorporate freight transportation. Solid blocks indicate SAMS components.

Fig. 1. Sequenced activity-mobility simulator (SAMS).*

Paradigm shifts embodied in SAMS

SAMS is fundamentally different from conventional transportation forecasting model systems in several crucial aspects. The key paradigm shifts embodied in the SAMS modeling framework are summarized in Table 1. The central distinguishing features of SAMS are the use of stochastic microanalytic simulation forecasting and dynamic modeling based on longitudinal data collection and analysis (for further discussions see Goodwin et al., 1990; Goulias & Kitamura, 1992). In addition, SAMS incorporates an activity-based, rather than a trip-based, approach to travel modeling; it adopts satisficing, as opposed to optimizing, as the principle that describes individuals' behavior (discussed in the Section for "The activity-mobility simulator (AMOS): A key component of SAMS"); it envisions the use of GIS-based spatial analysis, rather than zone-based analysis; and it incorporates endogenous forecasting of socio-demographics, land use and vehicle transactions.

Table 1. Paradigm shifts embodied in the SAMS modeling framework.

Existing approaches to transportation modeling	SAMS Modeling approach
Aggregate extrapolation forecasting	Microanalytic simulation forecasting
Static models, based on cross-sectional data	Dynamic models and processes, based on longitudinal data
Trip-based travel model	Activity-based travel model
Optimizing behavior assumed (e.g., discrete choice models, network equilibrium)	Adaptation and satisficing behavior assumed
Zone-based geographical representation	Point-based geography, based on GIS platform
Exogenous input of land-use, socio-demographic and vehicle characteristics	Endogenous modeling of land-use, socio-demographic and vehicle characteristics

Underlying SAMS is the transition from deterministic, aggregate extrapolation to stochastic, microanalytic simulation forecasting. The motivating factor for the adoption of microsimulation as a central driving force of SAMS is the fact that activity-travel behavior is a multi-dimensional process that is governed by layers of constraints and influenced by numerous factors, many of which are stochastic. Arranging activities and trips into a daily itinerary itself is a complex operations research problem to which individuals have devised routines to find a (not necessarily optimum) solution. Despite the simplicity of the activity-based approach that arises from its focus on human behavior without introducing artificial constructs, the behavior under investigation is indeed complex to analyze. Given the complexity and stochastic elements inherent in transportation system performance, constraints and motivating factors for activity-travel behavior, and in human decision and behavior themselves, microsimulation is the only feasible approach that need not embrace over-simplifying assumptions that reduce the realism in the travel behavior being represented by the model.

Immediately following the shift to microanalytic simulation forecasting is the paradigm shift from the use of geographical zones as the unit of analysis to point-based geographical representation using a GIS platform. Micro-simulation of individuals' behavior can be best achieved by having disaggregate representation of transportation networks and land use as this would facilitate the simulation of the precise trajectory of the individual in time and space and the explicit linking of the activity type and land use type at an adequate level of disaggregation.

Another critical paradigm shift is from static analysis and modeling based on cross-sectional data to dynamic analysis and modeling using longitudinal data. This shift reflects a skepticism of the well-accepted and well-practiced, yet not validated assumption, that future behavior can be predicted based on the extrapolation of cross-sectional observations. Application to forecasting of a model estimated on a cross-sectional data set taken at one point in time, represents the "longitudinal extrapolation of cross-sectional variations" (Kitamura, 1990) in which cross-sectional elasticities observed across different individuals are applied as if they represent longitudinal elasticities that capture the change in behavior that follows a change in a contributing factor within each behavioral unit. This approach is valid only under very restrictive conditions (Goodwin et al., 1990). For example, it requires that behavioral response is immediate without involving any time lag; that the magnitude of response is invariant regardless of the direction of change; and that behavioral response is independent of the past history of behavior. The very assumption of the equivalence between cross-sectional and longitudinal elasticities has yet to be validated, while empirical evidence is accumulating that this assumption does not hold in general (Kitamura & van der Hoorn, 1987; Goodwin, 1977).

A dynamic, longitudinal framework allows for the explicit incorporation of behavioral dynamics including lags and leads in response time, asymmetry in response, behavioral inertia and habitual behavioral patterns (e.g., brand loyalty). Furthermore, it permits the reformulation of behavioral models as dynamic decision models, in which decisions are made considering outcomes over a span of time, rather than as a series of repeated myopic choices. Realism is gained in the proposed approach because present decisions affect the future and are affected by decisions made in the past, as well as by expectations of the future (de Jong & Kitamura, 1992). Long-term decisions, such as vehicle holdings, employment, and residential location, may be modeled using intertemporal utility functions explicitly incorporating varying rates of time preferences. With the focus on behavioral dynamics, the time dimension is explicit in the entire model system.

The last paradigm shift to be discussed here is that SAMS internalizes the projection of the explanatory variables of its components through dynamic microsimulation, rather than relying on externally supplied, typically univariate projections. Applying dynamic models to forecasting calls for longitudinal projections of their explanatory variables. It is critical in this context that the multi-variate distribution of these variables be properly represented across behavioral units and over time periods. Unfortunately projections available to transportation demand forecasting have been marginal distributions of individual variables, e.g., age or income. Non-linear models, whether static or dynamic, require the joint distribution of all the explanatory variables defined for the behavioral unit, however. For example, if a model's explanatory variables include age, income, education, and distance to the nearest bus stop, then the joint distribution of all these four variables are needed to produce forecasts without aggregation bias. This problem has been recognized for disaggregate choice models, which are non-linear. The problem is compounded for dynamic forecasting because longitudinal projections of this joint, multi-variate distribution are needed. Microsimulation of demographic, socio-economic, land-use and other explanatory variables is proposed and incorporated as SAMS components as an approach to produce multi-variate, longitudinal projections of the explanatory variables.

SAMS organization and components

At the heart of SAMS is AMOS, a dynamic microsimulator of household activities and travel over time and space. The other model components of SAMS are: a socio-demographic simulator, an urban system simulator, a vehicle transactions simulator, a dynamic network simulator, and an emissions module. All spatial elements are manipulated in the simulation on a GIS platform without zonal aggregation. The output from these models is used to derive mobility, air quality, transportation system performance and welfare (time use utility) indices to be used in planning and policy analysis. It is important to note that the simulators operate at different time-scales, ranging from a very fine time increment (1 to 3 minutes) for AMOS and the dynamic network simulator, to a yearly time increment for the socio-demographic and urban system simulators.

Each of the key model components of SAMS is briefly described below, except for AMOS, which is discussed in detail in the Section for "The activity-mobility simulator (AMOS): A key component of SAMS". We first discuss the simulators for the processes that operate at more coarse time-scales.

The socio-economic and demographic simulator
The socio-economic and demographic simulator is a stochastic microsimulator of the socio-economic and demographic evolution of households and firms. The latter are the drivers of long-range changes in regional economy and land use. That is, this simulator provides the basic parameters (e.g., population, income, employment levels) to determine each sector's demand for vehicles, activity participation and related travel and location choices.

The household component will aim to replicate the progression of a household through the life-cycle stages (e.g., young single person, young couple, family, old couple, old single person, etc.) and simulate changes in each person's socio-economic attributes (e.g., age, education, employment, driver's license holding) based on their stage in the life-cycle. This general structure is employed in each of the existing transportation-related microsimulation models (Mackett, 1985, 1990; Miller et al., 1987; Goulias & Kitamura, 1992). This component will consist of a series of sub-models that simulate changes in socio-economic and demographic variables pertinent to mobility decisions.

The business component of this model will simulate the birth, growth and death of firms in terms of pertinent variables such as number of employees, size and location. While we know of no such model in existence, we believe such a model can be initially developed as a descriptive simulator that replicates observed dynamics in a firm's economic and spatial behavior.

The urban system simulator
A recognized weak link in the conventional transportation forecasting model is the inadequate representation of the interaction between land-use and transportation. Further, it is well known that existing land-use models do not represent the demand for and supply of urban land in a market context and thus land prices and rents are not adequately incorporated in such models.

The urban system simulator will be a dynamic, market-based microsimulator of urban evolution representing the household, commercial/industrial, and developer sectors where land prices and rents are endogenously forecast through market-based land transactions simulation. Household residence and job location choice, firms' location decisions, and developers' development decisions will all be modeled at microscopic levels. Each unit's search and transaction behavior will be simulated to form a market model that replicates selling, buying, development and redevelopment decisions, within anticipated zoning and other restrictions.

The vehicle transactions simulator
Most existing discrete-choice models of household vehicle ownership are cross-sectional vehicle holdings models that describe the likelihood that a household of given attributes will hold a particular set of vehicles. While

such models have quantified the effects on vehicle demand of various vehicle attributes and household socio-economic characteristics, they contain limitations that may restrict their usefulness in forecasting.

First, the number of household vehicles that can be handled is usually limited to two, because the number of alternatives in such models becomes astronomical when the fleet size exceeds two. Second, vehicle holdings models take the viewpoint that a household compares vehicle fleets of different composition and selects the most suitable fleet. Such models are based on the implicit assumption that the household compares the "utilities" of the alternative fleets and chooses the one with the highest utility. This assumption, however, is not realistic, because the household acquires, replaces, and disposes of vehicles sequentially over time and the household fleet might not be optimum at a particular point in time. Third, vehicle holdings models estimated using cross-sectional data are essentially static and are therefore unable to forecast how quickly new types of vehicles will penetrate the market. However, this ability is critical in connection with analysis of the effectiveness of low- and zero-emission vehicles.

The vehicle transactions simulator is a dynamic, stochastic microsimulator of the time-path of vehicle fleet rejuvenation based on models of decisions to acquire, dispose and replace vehicles, and the choice of vehicle types. By focusing on transaction decisions, such models offer new possibilities to correct many of the deficiencies of vehicle holdings models. Most importantly, a large number of household vehicles can be easily incorporated, and the frequency of transactions is explicitly modeled. They also allow the representation of vehicle ownership cost as an endogenous variable that is a function of the holding duration. For further discussions on the advantages of vehicle transactions models, see de Jong & Kitamura (1992). Examples of household vehicle transactions models can be found in Hocherman et al. (1983); Smith et al. (1989) and Hensher (1994). These models, however, address only limited aspects of vehicle transaction behavior (e.g., replace a vehicle vs. do not replace a vehicle). An ongoing model development effort that attempts to develop a full-fledged vehicle transactions model system is described by Golob et al. (1992).

Dynamic network simulator

The dynamic network simulator is closely intertwined with AMOS and operates on a continuous 24-hour time axis to provide temporal variations in traffic flow characteristics. This is made possible by the fact that AMOS offers output of travel demand on a continuous time-of-day basis, and therefore the network assignment in SAMS takes as input non-stationary traffic volumes and represents the build up and dissipation of traffic congestion.

While the development of dynamic network assignment algorithms is a challenge, advances in computer speed and dynamic network assignment methodology promise that truly behavioral network assignment is possible while incorporating realistic models of route choice behavior. That is, the modeling approach may emphasize the availability of information, learning and satisficing (as opposed to the currently prevailing assumption of equilibrium) when constructing route choice models for pre-trip as well as en-route decisions.

The proposed microsimulation approach has many advantages, including the ability to model the driver's response to traffic information, a capability that is invaluable in analyzing the effectiveness of advanced route guidance systems. Another important advantage of micro-time increment network simulation is the ability to suitably represent traffic conditions at critical locations (e.g., carbon monoxicide "hot spots"). Examples of the use of this capability include pollutant emissions due to vehicles queued at a metered on-ramp, congested intersections, or up-grade on-ramps where acceleration takes place. The proposed network microsimulator will also serve as a valuable experimentation ground for the development of incident management strategies, and determining the optimal placement of detectors and other traffic surveillance devices.

It is recognized that development of this network microsimulator presents a significant challenge and may take some time. A number of efforts are currently underway to address the development of dynamic network simulation. In the interim, it is suggested that creative use be made of existing equilibrium assignment packages.

The activity-mobility simulator (AMOS): a key component of SAMS

AMOS is an activity-based model of travel decisions that captures pertinent factors at work in the adaptation of activity engagement, scheduling and travel behavior exhibited by individuals and householders. The approach is necessarily microscopic and individual-based because an adequate forecasting procedure and policy tool can be formulated only through rigorous analysis and modeling of decision-making units. Below, we highlight the behavioral underpinnings of AMOS and then provide a brief introduction to each of the AMOS model components.

The behavioral underpinnings of AMOS

The key paradigm shifts embodied in AMOS are described in this section, including the central premises of the activity-based approach to travel demand analysis and the key concepts related to adaptation behavior.

The central premises of the activity-based approach

The intent of activity-based travel analysis (Jones et al., 1983; Kitamura, 1988a; Pas, 1990; Jones et al., 1990; Axhausen & Garling, 1992) is to provide a conceptual structure that represents the mechanism of trip making in a more fundamental and comprehensive manner than trip-based procedures allow. Because trips are made in order to engage in activities, the best account for trip making can be achieved by analyzing and explaining individuals' and household members' activity engagement. That is, travel behavior can be best understood by examining how engagement in discretionary activities is decided, how in-home and out-of-home activities are traded off, how the location of each activity is chosen, how allocation of time to various activities is adjusted to accommodate for a loss or gain of discretionary time, and how household members interact in their activity engagement decisions.

Activity engagement is synonymous with time use. By analyzing the patterns of time use and revealing the underlying decision structure, it is possible to construct a model system for activity engagement. Also by analyzing the parallel and inter-related decision of location choice for each episode of activity, it is possible to thoroughly account for the generation of trips. These two combined can be used to determine how changes in time availability caused by changes in the travel environment (e.g., increased or decreased levels of congestion) may affect overall time use and travel patterns. For example, Kitamura et al. (1992) and RDC (1993b) examined the relationship between commute trip duration and time allocation to discretionary activities and travel. In fact, the most rigorous treatment of the issue of induced (and suppressed) travel can be attained by analyzing time use. Additional examples include congestion pricing, non-traditional work schedules (e.g., flexible work hours or compressed work weeks), and the examination of individuals' responses to these new TDM schemes over a multi-day period (say, a week). For an overview of time use research and its potential in travel demand analysis, see Pas & Harvey (1995). The needs to examine the relation between activity choice and location choice have been identified by Landau et al. (1981). To the knowledge of the authors, no study has examined how the transition between activity episodes is related to the change of activity locations.

The activity-based approach facilitates an accurate depiction of an individual's response to a change in the travel environment in contrast to the current generation of models. In the trip-based, four-step approach, the adaptation process is decomposed and represented by changes in trip frequency, destinations, modes and routes, without any coherent relationships among these attributes, without any recognition of the cognitive process that leads to changes in behavior, and above all, without any regard to the reasons why trips are made. The behavioral responses captured by the four-step procedures include only a partial list of a wide range of response patterns; uncaptured responses include decisions to chain trips, to change departure time, or to consolidate chores into selected days of the week.

The activity-based approach can accommodate the effects of interpersonal dependencies that exist among household members as they negotiate resources (e.g., household vehicles and incomes), allocate tasks (e.g., paid-work and running errands), and engage in joint activities (e.g., a Sunday outing) to arrive at an overall pattern of activity engagement and travel behavior (Pas, 1985). This perspective has led to the identification of household life-cycle stage, and particularly the presence or absence of children, as one of the key contributing factors to travel behavior (Jones et al., 1983).

Another distinguishing feature of the activity-based framework for travel analysis is its focus on inter-day dependencies (Pas, 1985). Individuals and households schedule their activities over time spans that are longer than a day; some activities may be scheduled with a weekly cycle (e.g., shopping) while others are planned over much longer periods (e.g., an out-of-town trip or a vacation, see Hirsh et al. (1986); Kitamura (1988b); Pas (1988). Understanding the scheduling behavior by which activities and travel are assigned to different days is imperative for the incorporation of the day of week into the travel demand forecasting procedure. Furthermore, it is believed that intensifying congestion, labor-force participation by women, non-traditional work schedules, and some TDM strategies will lead individuals to consolidate certain activities on certain days or to change the day of travel. Accurately accounting for inter-day dependencies in activity and travel is another focus of the modeling approach outlined in this paper.

A variety of "constraints" are highlighted by the activity-based approach to travel analysis (Jones et al., 1983). All individuals are constrained by the fact that there are only 24 hours available in a day; workers by their work schedules; shoppers by store hours; parents by operating hours of the day-care facility; bus users by bus routes and schedules; and minors by the fact that they cannot drive. Individuals and households attempt to devise a workable plan for their activity engagement while being governed by the constraints. Although constraints play predominant roles in shaping an individual's activity and travel behavior, they have received only very limited attention in the past (car availability in mode choice appears to be the only occasion where constraints are routinely incorporated into the analysis).

The behavioral principle of adaptation

AMOS is a microsimulation model where adaptation behavior is treated as a learning process in which the individual gains knowledge about various aspects of the new travel environment as he/she attempts to adapt to it. Adaptation behavior is viewed as a trial-and-error process in which the individual tries out alternative activity-travel options until a suitable option is found. To the knowledge of the authors of this paper, however, no quantitative models have been developed so far that operationalize the adaptation concept and are applicable to demand forecasting and quantitative policy analysis. AMOS is believed to be the first model system that achieves this.

While the concept of adaptation was introduced into the field almost 20 years ago (Fried et al., 1977), it did not assume a central role until recently (Goodwin et al., 1992). Adaptation is a central concept in AMOS, and the activity-based framework provides for a broad range of adaptation strategies. An individual can respond to a change in the travel environment in many different manners that cannot possibly be captured as independent changes in trip frequency, destination, mode, and route. By examining how the individual may adapt to a new travel environment by modifying his/her activities in time and location, a more comprehensive treatment of travel demand becomes possible and a more realistic depiction of adaptation processes can be achieved.

Although a few principles are conceivable (e.g., minimization of adjustment costs, minimization of behavioral changes), to the knowledge of the authors none has previously been postulated in the travel behavior analysis field for adaptation (except the principle implicit in the extrapolation of cross-sectional relations into the future which posits that the same relationships which characterize behavioral change over time can be observed in cross-sectional data). The optimization principle has often been applied to describe observed behavior. Its application, however, is justifiable only as an *operational* (as opposed to behavioral) axiom with the premise that a central tendency exists and embodies the optimization principle, and that deviations of individual observations from that central tendency can be accounted for by error components. This premise, however, is valid only when deviations from the central tendency are purely random.

This assumption of optimization is unrealistic as a behavioral axiom when applied to everyday behavior of activity engagement and travel by individuals and households. For example, the individual must possess complete information to be able to locate an optimum solution, and must be capable of sorting out an enormous number of possible options and discriminating among them. Optimization also assumes that the individual can perfectly detect minute differences among options. Practical decision-making is only loosely related to this ideal. Optimization thus assumes superhuman abilities in ordinary travelers and is unrealistic as a behavioral proposition. The information we have is partial and incomplete; the number of items we can incorporate into our cognitive system is limited; our perceptive ability to discriminate between stimuli is limited; the outcome of a decision is usually highly uncertain; and our decisions may not be internally coherent and consistently rational. Moreover, there is evidence that behavioral inertia is prevalent, and that we tend to resist behavioral changes. Our travel behavior is most probably not in the state of equilibrium which the paradigm of optimization assumes (Goodwin et al., 1987).[2]

The development of AMOS reflects the intention to adopt the most realistic modeling framework that best replicates activity-travel behavior. Instead of assuming the presence of cross-sectional equilibrium based on optimization, the behavioral process of adaptation is explicitly modeled in AMOS. In AMOS, adaptation simulates a trial-and-error learning process based on "satisficing" as the governing behavioral principle (Simon, 1955). It is important in this context to recognize that there may exist many different adaptation principles that direct each individual's behavior. Even the same individual may follow different principles from situation to situation. This likely heterogeneity in the causal mechanisms underlying adaptation behavior or, "causal heterogeneity" (Pendyala, 1992), must be properly addressed in future efforts.

Asymmetry and slow or cumulative changes
Among the behavioral dynamics associated with the adaptation process are asymmetry in people's behavior and differences in people's adaptation behavior in response to slow or cumulative changes in the environment. Individuals' and households' response to a change may not be symmetric, i.e., response characteristics may vary depending on the direction of the change in the environment. There are many reasons for asymmetric behavioral response. First, apparent asymmetry may be a result of differences in the speed of response. Individuals may respond more quickly to a change in one direction than to one in the other direction. For example, a household member gaining employment may lead to immediate acquisition of an automobile because it is needed to commute, but a member losing employment may not necessarily lead to the disposal of a household vehicle because the vehicle, once acquired, can be retained at a low marginal cost. Finally, asymmetry can also be due to differences in thresholds of perception, i.e., changes in one direction may be more noticeable than those in the other direction. For further discussions, see Kitamura & van der Hoorn (1987).

Change in the travel environment is not always sudden; some slow changes are appreciable only after their effects have accumulated over time (Goodwin et al., 1992). Response time lags are intrinsic in the adaptation to slow or cumulative changes. The central issue in adaptation to slow changes revolves, then, around the perception of changes. Until there is such a perception, a response or adaptive behavior won't ensue. A key element is the threshold of perception, and how it is related to the rate of change in cases of cumulative changes. For example, at what point is ever increasing commute travel time due to congestion perceived as intolerable, and at what point will that perception lead to an adaptive behavior such as residential relocation or mode change? And how is all this related to the rate at which congestion has been building up? Likewise, there are small changes that may take place over a span of time and which are singly insignificant, but which collectively command response. For example, a new baby in the family may not alone prompt acquisition of a new car, but this combined with the mother going back to work may warrant the acquisition. Additional complexity arises when considering the role of information and uncertainty in the formation of perceptions. Modeling adaptation to slow, and/or cumulative changes is a new research area in which much work is needed in the future to address these and many additional issues.

Components of AMOS

Starting from an initial set of activity-travel patterns, AMOS simulates each individual's adaptation process and finally determines how individuals and households will adapt to the new environment. The first event that must take place for behavioral change to proceed is that the individual recognizes the change in the travel environment and perceives the need for behavioral modification. Given this, a search for a desirable behavioral modification commences with the identification of possible response options. This is not a systematic, exhaustive procedure; individuals will operate with imperfect information and will be unable to systematically enumerate all possible options. Once an individual identifies a response, or a preferred set of responses, the next step is to try out the options, one at a time, until a "satisfactory" pattern is established. This experimentation process is represented by repeating the simulation procedure for a period adequate to achieve stability.

AMOS is comprised of four major elements that operate in an iterative procedure: a baseline activity-travel pattern synthesizer, a response option generator, an activity-travel adjuster, and an evaluation routine. These elements are described in the following sub-sections. Figure 2 illustrates the organization of the AMOS model.

The baseline activity-travel pattern synthesizer. The impact of a change in the travel environment is evaluated in AMOS by estimating, for each household or individual, changes in the activity-travel pattern from the baseline pattern. The latter is developed from observed daily travel patterns contained in typical trip records (e.g., purpose of the trip, travel mode used, departure and arrival times, origin and destination zones, vehicle occupancy, and parking characteristics). These records facilitate the reconstruction of the household members' travel patterns over the geographical space along a continuous time dimension. Combined with land use and network data, trip diary data generate an adequate data base for the analysis of household responses to TDM

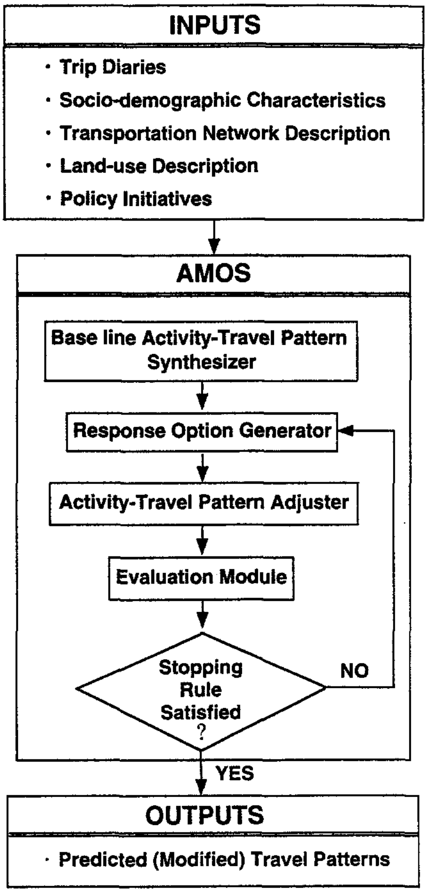


Fig. 2. Activity-mobility simulator.

measures. The synthesizer identifies the types and durations of out-of-home activities from the trip record of each individual, and determines, based on a set of rules, types of constraints associated with the trips made (e.g., the individual must arrive at work no later than the arrival time of the work trip found in the trip record; see discussions under "The Activity-Travel Adjuster").

The response option generator. The purpose of this component is to generate and prioritize a series of options that individuals are likely to consider when faced with changes in their travel environments. The intent is to simulate the cognitive process in which each individual devises alternate options, prioritizes them and selects possible options. Generating possible travel options is viewed here as the first step in the process of adapting to the new travel environment. Response options include those identified earlier, e.g., chain trips, change trip frequency, change departure time, change mode, or any combination of these responses, plus doing nothing (i.e., to maintain the same activity-travel pattern).

The method of generating options is based on connectionism theory. Connectionism is an approach in the study of cognition. Benjafield describes it as: "the two basic connectionist ideas are that information can be broken down into elements, and that there are connections between these elements. These connections can have different strengths, and the (model) system learns by modifying the strength of connections between elements so that proper output occurs to a particular input." In this approach, thinking is viewed as the process of linking objects or concepts with certain patterns (Benjafield, 1992, p. 38).

This idea leads to the formulation of "connectionist networks," which can be viewed as a special case of neural networks. Connectionist networks are used in AMOS to determine which response options an individual may conceive as a result of changes in the travel environment. Input to the connectionist network will be pertinent person and household attributes, travel characteristics and potential changes in the travel environment (e.g., congestion pricing) and output will be response options (e.g., chain trips) individuals may conceive and prefer to take. Each input and output are represented by a node. Between the input and output nodes are intermediate "latent" nodes, which represent the consequences of a change in the environment (e.g., increased inconvenience, etc.). The network can be "trained," i.e., the strength of the link connecting each pair of nodes in the network is determined such that the network will best replicate input-output relationships exhibited by individuals. This can be achieved using data obtained from interview surveys specifically designed for this purpose.

The activity-travel adjuster. Once the individual sorts out what options are available, the next step is to experiment with the options. In AMOS, a micro world is created on the computer in which daily travel experience is simulated for each sample individual and for each option that might be taken.

AMOS employs a screening procedure to eliminate infeasible activity-travel patterns that may result from the option chosen by each individual. The screening process will be based on a set of rules, e.g., drivers who need to drop off children at day care will not be able to make certain changes in their baseline travel pattern. In other words, the screening process will limit the potential responses that a particular individual can actually execute given their situational constraints.

Feasible activity-travel patterns will then be simulated initially based on trip-time tables by time of day and by mode, and ultimately on a GIS-based urban highway/transit network model using dynamic network assignment. This network simulation will provide the actual travel time and arrival time for each trip, and thus will generate events such as "arrived five minutes late for work," or "arrived 20 minutes too early." In short, this step will create, on computer simulation, what the individual would experience if they adopted a particular option. (It is anticipated that computational requirements for such dynamic network analysis will be met within the next several years, and will enable the microsimulation of all trips in an urban network. For ongoing effort, see Barrett et al. (undated.)

The simulation will involve all sample individuals in the data base (which may be expanded with synthetic individuals), from different home locations, different demographic and socio-economic attributes, different constraints and different activity agendas. Their trips are properly weighted to represent the population of the area, and "loaded" onto the transit and highway network such that link volume, speed, and travel time can be evaluated through network simulation. Note that the outcome for an individual will depend on the behaviors of the other individuals; the simulation thus captures supply-demand relationships in transportation networks. This is crucial in the analysis of some TDM strategies such as congestion pricing.

The evaluation module. Knowing the consequences of an option, the individual would now proceed to decide whether the option is: satisfactory and is acceptable for long-term adoption; to be modified and further pursued; or inadequate, and thus to be abandoned in favor of a new option. The focus of this component is on the development of measures that may be used to determine how good a particular adjusted activity-travel pattern is, or more precisely, how good the outcome of that option is in the individual's eye. It is desired that the measure represents the value system the individual has, as closely as possible. At the same time, the measure must be prescribed in terms of well defined, measurable variables such that its value can be objectively evaluated and used in forecasting.

Note that the individual may not be looking at just travel alone, but the entire itinerary of the day including both trips made and activities undertaken. Also note that what matters to the individual is the value of the activities engaged in and the convenience and ease of doing so, which is in part determined by trip characteristics. Therefore, it is critical that the evaluation measure reflect the types of activities pursued, the amounts of time allocated to the respective activities, the timing of the activities, as well as the attributes of the activities and travel. Finally, it is also critical that differences across segments of individuals or households be properly captured by the measure.

Two approaches are conceivable for the development of a robust evaluation measure. The first approach, which is being implemented, capitalizes on the results of a time use study in which consumer benefit measures have been developed based on daily time use and on a utility model of time use (RDC, 1993b). The second is a stated-preference (SP) approach based on a survey formulated to address time-money trade-offs, as well as preferences toward activity timing and activity sequencing. One advantage of the latter approach is its ability to focus on specific aspects of interest that may be difficult to evaluate from revealed-preference (RP) data, e.g., scheduling flexibility and convenience.

Discussion and conclusion

This section addresses a number of outstanding issues that are involved in the development and implementation of the type of integrated, complex and dynamic framework that SAMS represents. An overview is provided in this section of the general types of data required, and data collection methods being adopted for SAMS' development. The section concludes with a summary of the capabilities and paradigm shifts that SAMS presents to transportation, land use and air quality planning and policy analysis.

The development and validation of SAMS requires extensive and diverse information. A new layer of data requirements emerges with the microsimulation approach that is at the core of SAMS, calling for innovative approaches in the collection of complex behavioral data. Confining ourselves to the development and validation of AMOS, which is in an advanced stage of development, three types of data are required:

1. reported behavioral data (often called revealed-preference data) and demographic and socio-economic data from those who report their behavior;
2. observational data (e.g., link flows and travel times, network structure, household turnover rates, etc.);
3. data describing respondents' stated intention about how they would react to changes ("stated adaptation" data; see Lee-Gosselin, 1995), as well as their preferences for alternative activity and travel options, e.g., activity timing, sequencing, etc. (called stated-preference data).

SAMS is a dynamic model system; therefore, longitudinal data are needed for the development as well as validation of the various modules (with the possible exception of network simulation and the emissions module). The demographic and socio-economic simulator, land use simulator, and vehicle transactions model all require longitudinal panel data to develop and validate. The development and validation of the adaptation process model in AMOS will greatly benefit from short-range longitudinal panel data of the "before-and-after" type and from data collected through laboratory experiments that simulate adaptation processes on a compressed time scale in a hypothetical environment (see, for example Ettema et al., 1994).

Stated preference surveys specifically designed for AMOS development are being used not only to obtain respondents' preferences and reactions toward, for example, congestion pricing, but also to examine preference structures in connection with time use and scheduling.[3] In particular, stated preference questions can be structured to probe into the cognitive process underlying individuals' adaptation processes.

Time use diaries are being used as part of SAMS development in a project implementing an AMOS prototype. The time diary method offers the possibility of a fuller, more detailed and more complex account of travel-related behavior because respondents are asked to provide a continuous recollection of all activity across the day. In this way, it forces respondents to report the totality of their daily activity into a single account, one that for most people is more in line with the way events are stored sequentially in memory. The open-ended nature of activity reporting means these activity reports are automatically geared towards detecting new and unanticipated activities (e.g, aerobic exercises, use of new communications technologies, etc.), as well as capturing the context of how daily life is experienced.

SAMS is conceived as a large-scale, integrated model system comprised of a number of modules. The development, validation and implementation of the complete model system will take a number of years. The fact that SAMS is an innovative model system that is based on an entirely new set of paradigms implies the presence of a number of research issues. For example, satisficing rules must be developed for AMOS (laboratory experiments are being designed to probe into travelers' experimentation and learning behavior); evaluation functions to assess the utility of activity-travel patterns must be developed while considering time use, scheduling convenience and travel costs; mechanisms must be developed for the generation of synthetic households and activity-travel patterns; inter-personal interaction must be represented in AMOS to depict household behavior; and the modeling framework in AMOS must be expanded to address multi-day activity-travel behavior. However, elements of the model system can be developed and implemented in the short- to medium-term, either in conjunction with more traditional model systems or used on their own in the analysis of specific policy questions.

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Notes

1. Detailed discussions of SAMS development can be found in RDC (1992) and RDC (1993a).
2. For an example of an activity scheduling model system based on optimization, see Recker et al. (1986a, 1986b). An extensive review of activity scheduling models can be found in Garling et al. (1994).
3. The stated adaptation survey which was conducted as part of the ongoing implementation effort of AMOS in the Metropolitan Washington Council of Governments area include the following TDM strategies: i) parking tax; ii) bicycle/pedestrian facility improvements; iii) combination of i and ii; iv) employer-supplied travel voucher with elimination of employer-supplied free parking; v) congestion pricing; and vi) combination of iv and v.

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