4. Historical Development of Activity Based Model Theory and Practice*

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This article discusses the theory underlying activity based (AB) travel demand modelling; important steps in its move from theory into practice, with a focus on developments occurring in the United States, the United Kingdom and Europe; and features of models systems in use in the United States.

Activity Based Travel Theory

One of the most fundamental and oft-quoted principles is that travel demand is derived from activity demand (Jones, 1979). This principle implies a decision framework in which travel decisions are components of a broader activity scheduling decision, and calls for modeling activity demand. Chapin (1974) theorized that activity demand is motivated by basic human desires, such as survival, social encounters and ego gratification. Activity demand is also moderated by various factors, including, for example, commitments, capabilities and health. Unfortunately, it is difficult to model the factors underlying this demand, and little progress has been made in incorporating the factors in travel demand models. However, a significant amount of research has been conducted on how household characteristics moderate activity demand. This research concludes that (1) households influence activity decisions, (2) the effects differ by household type, size, member relationships, age and gender, and (3) children, in particular, impose significant demands and constraints on others in the household (Chapin, 1974; Jones, Dix, Clarke and Heggie, 1983; Pas, 1984).

Hagerstrand (1970) focused attention on constraints--among them coupling, authority, and capability--which limit the individual's available activity options. Coupling constraints require the presence of another person or some other resource in order to participate in the activity. Examples include participation in joint household activities or in those that require 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 the limits of nature or technology. One very important example is the nearly universal human need to return 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.

The conceptual work of Hagerstrand (1970), Chapin (1974) and others, summarized nicely by Jones (1979), lead to an extensive amount of descriptive empirical research on the relation of human activity and travel behavior, providing additional insights into the

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* Material in the first two sections of this article draws heavily on prior reviews by Ben-Akiva and Bowman (1998) and Bowman and Ben-Akiva (2001).

nature and complexity of activity and travel decisions. Damm (1983), Golob and Golob (1983), Kitamura (1988) and Ettema (1996) provide extensive reviews of the literature on activity-based travel theory. We present here only a few highlights. Pas (1984) finds demographic factors such as employment status, gender and presence of children to have significant effects on the choice of the activity and travel pattern. Pas and Koppelman (1987) examine day-to-day variations in travel patterns, and Pas (1988) explores the representation of activity and travel choices in a week long activity pattern. Kitamura (1984) identifies the interdependence of destination choices in trip chains. Kitamura, et al (1995) develop a time and distance based measure of activity utility that contrasts with the typical travel disutility measure. Hamed and Mannering (1993) and Bhat (1996) explore methods of modeling activity duration. Bhat and Koppelman (1993) propose a framework of activity agenda generation.

The concepts of AB demand, and time and space constraints, have also been incorporated in the classical model of the budget constrained utility maximizing consumer. Becker (1965) made utility a function of the consumption of commodities that require the purchase of goods and the expenditure of time. DeSerpa (1971) explicitly identified the existence of minimum time requirements for consumption of goods. Evans (1972) generalized the model, making utility a function only of activity participation; formulating a budget constraint based on a transformation which relates the time spent on activities, the goods used in those activities and the associated flow of money; and introducing coupling constraints which, among other things, allow the explicit linking of transportation requirements to the participation in activities. Jara-Diaz (1994) extended an Evans type model to explicitly allow the purchase of goods at alternative locations, each associated with its own prices, travel times and travel costs, all of which enter the time and budget constraints. He also included a transformation relating the purchase of goods to required trip-making. In maximizing utility, the consumer chooses how much time to spend on various activities, how many trips to make overall, what goods to buy and where, and the travel mode for each trip. These theoretical models stop short of addressing important aspects of the scheduling problem, such as temporally linking activities or allowing for the chaining of trips between activity locations.

Figure 1 shows how activity and travel scheduling decisions are made in the context of a broader framework, surrounded by and connected to other relevant decisions (Ben-Akiva, 1973; Ben-Akiva and Lerman, 1985; Ben-Akiva, Bowman and Gopinath, 1996).

Urban development decisions of governments, real estate developers and other businesses influence the opportunities available to households and individuals. Governments may invest in infrastructure, provide services, and tax and regulate the behaviour of individuals and businesses. Real estate developers provide the locations for residential housing and businesses. A firm's location choice and its production decisions affect job opportunities in that area.

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 decision making. Mobility and lifestyle decisions occur at irregular and infrequent intervals, in a time frame of years. These decisions are exemplified by household composition and roles, workforce participation, workplace, domicile, and long term activity commitments, as well as a set of long term transport decisions: auto ownership, work commute mode, transit and parking arrangements, commute program participation, and, potentially, the acquisition of equipment for automated traveller information systems.

Activity and travel scheduling, a planning function, occurs at more frequent and regular intervals. It involves the selection of a particular set of activities and priorities, assignment of activities to particular members of the household, sequencing of activities, and selection of activity locations, times and methods of required travel. In AB models it is often conveniently assumed that the activity and travel scheduling decision addresses a 24-hour day.

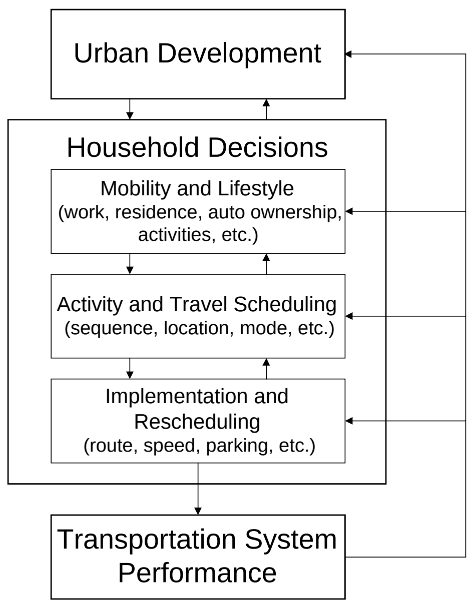

Figure 1 Activity and travel decision framework . Many household decisions, occurring over a broad range of timeframes, interact with each other and with the urban development process and transportation system performance.

Within the day, unplanned implementation and rescheduling decisions occur; these include en-route choices of route, 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; taken together, urban development and individual decisions affect performance of the transportation system, such as travel volume, speed, congestion and environmental impact. At the same time, transportation system performance affects urban development and individual decisions.

From Theory to Practice

The previous section's examination of theory provides the concepts needed for examining AB modelling approaches. In the last 35 years modelers have attempted to incorporate the insights gained on activity-based travel theory into urban travel forecasting models, with increasing success enabled by the advance of computing technology. Here we mention a few operational forecasting systems representative of the most advanced practice of their time worldwide.

Integrated Trip-based Models (1970s and 1980s).

The MTC system (Ruiter and Ben-Akiva, 1978; Ben-Akiva, Sherman and Krullman, 1978) was developed for the San Francisco Bay Area, and used in forecasting for many years. It is estimated as an integrated disaggregate choice model system. Models include accessibility variables representing expected maximum utility derived from related conditional models. The linkages across models introduce a partial representation of time and space constraints and household interactions. However, the system ignores some natural time and space constraints by modeling trip decisions separately—hence the label "trip-based"—and excluding the modeling of duration and time of day. Horowitz (1980) presents a trip frequency, destination and mode choice model that incorporates inter-trip dependence and can be implemented in a trip-based model system.

Tour-based Models (1980s and 1990s).

Tour-based systems were first developed in the late 1970's and 80's in the Netherlands (Daly, van Zwam and van der Valk, 1983; Gunn, van der Hoorn and Daly, 1987; Davidson and Walker, 1990; Hague Consulting Group, 1992; Gunn, 1994). Subsequently, tour-based model systems were developed and used for Stockholm (Algers, Daly, Kjellman et al., 1995), Salerno, Italy (Cascetta, Nuzzolo and Velardi, 1993), and the Italian Transportation System (Cascetta and Biggiero, 1997). These models group trips into tours based on the fact that all travel can be viewed in terms of round-trip journeys based at the home. A tour is assumed to have a primary activity and destination that is the major motivation for the journey. Some of these models introduced the explicit representation of joint travel among household members.

The modeling of tour decisions provides an incremental improvement over trip-based model systems, incorporating an explicit representation of temporal-spatial constraints among activity stops within a tour. However, the tour-based approach lacks a connection among multiple tours taken in the same day, thereby failing to capture the effects of inter-tour temporal-spatial constraints.

Pre-cursors of Full-Day Model Systems (1980-1995)

Beginning in the late 1970s, significant attempts were made to broaden the scope of forecasting models to incorporate activity and travel decisions spanning an entire day. Some of these rely primarily on econometric choice models and the theory of the utility maximizing consumer, as did the preceding trip-based and tour-based models, while others use rule-based decision simulations.

Among the econometric models Ben-Akiva et al. (1980) developed two interrelated models to represent a time budget and activity schedule. Adler and Ben-Akiva (1979) developed a model of a one-day non-work travel patterns. The choice of travel pattern is modeled as a single complex decision, in which many component decisions together define a day's travel. Hamed and Mannering (1993) use a variety of econometric model forms to represent an individual's temporally sequential construction of an activity and travel schedule, including activity duration.

The earliest rule-based simulation model, STARCHILD (Recker, et. al.,(1986b; 1986a), takes a destination-specific household activity agenda—a list of planned activities—and models detailed activity and travel schedules for household members. Recker (1995) formalizes the STARCHILD approach with a mathematical program that also addresses activity and vehicle allocation. Axhausen et al. (1991) propose a simulation model in which a sample of simulated households is used to model the evolution of travel behavior in daily, medium-term and longer time frames. RDC, Inc (1995) uses a two-stage model that includes a basic policy response and a heuristic search for a detailed schedule adjustment. Ettema et al. (1993; 1995) represent the scheduling decision as a sequence of schedule building decisions.

Full-Day Model Systems in the Laboratory (1994-present)

Broadening the decision scope to include activity decisions spanning a day or more is difficult because the variety of available schedules is immense. Accordingly, all the models in the previous section were developed only as incomplete prototypes, and rely on exogenous forecasts of important dimensions of the activity and travel scheduling decision, such as activity participation, location, and travel mode.

In contrast, in 1995 Bowman and Ben-Akiva (2001) presented the first working prototype of a full-day model that includes and integrates the activity participation decision for all activities and travel spanning a day, and also includes the dimensions of destinations, modes and timing of the associated travel. Since then, several model systems have been developed in academic settings that also provide a comprehensive representation of a person's day, and continue to advance the state of the art (see, for example, Bhat, et al, 2006; Pendyala, et al, 2004; Miller and Roorda, 2003; Arentze and Timmermans, 2000; Hensher and Ton, 2002).

Full-Day Model Systems in Practice (1997-present)

Within the consulting world, there have been an increasing number of model systems implemented primarily for practical use. These have been hybrid model systems, relying on econometric models that are integrated in a simulation framework using a blend of econometric principles and rule-based assumptions.

A Chronology

Figure 2 shows a timeline of the development and use of AB models. It includes only US projects, where a sponsor expressed the intent to implement and use the model, and development has started. This section briefly describes the innovations that have been implemented in these projects.

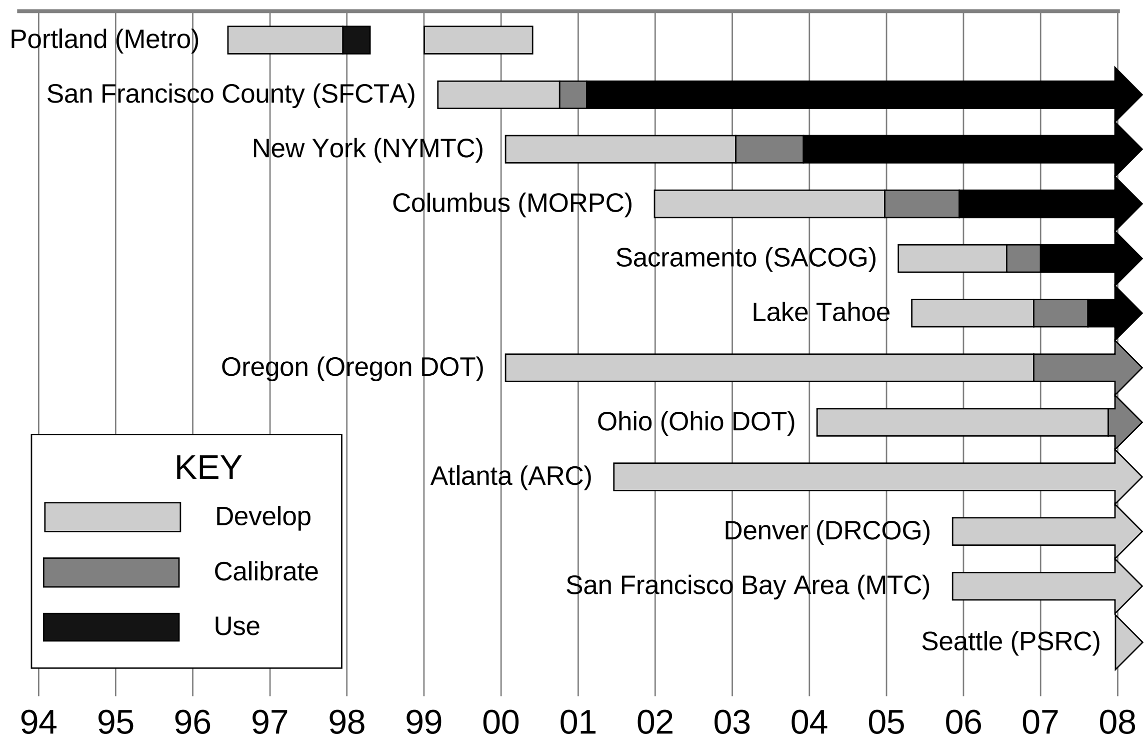

Figure 2 Timeline of AB Model Implementations in the United States

The Portland Metro model (Bowman, et al, 1998) was the first to be implemented and used for policy analysis. It was based directly on the Bowman and Ben-Akiva activity schedule approach developed at MIT, using a full-day activity pattern, conditional tour models, and sensitivity at the day level via logsums from the tour models. It introduced work-based subtours, at-home activities and detailed activity purposes, and integrated the AB model with the traffic and public transport assignment models.

The San Francisco County model used the same basic design. It was the first of the models to be calibrated, and then used on an ongoing basis for policy analysis. Along the way, innovative procedures were developed for doing that analysis. In a recent major project, the SFCTA model was enhanced to support road pricing, expand its geography, and add mode and temporal detail. It continues to be enhanced.

In New York, a different approach was used for integrating the tour models (Parsons Brinckerhoff, et al, 2005). Within each household, the simulated tour choices explicitly depended on the purpose of tours already simulated for this and other persons in the household. The NYMTC model has also been used for innovative analyses, some of which would not be possible with a traditional 4-step model.

The Columbus model (PB Consult, 2005) started with the NYMTC framework and enhanced it substantially, with a strong emphasis on implementing explicit household interactions and detailed time of day modelling.

The Sacramento model (Bradley, et al, 2006) also used the Bowman and Ben-Akiva activity schedule approach. It reformulated the day activity pattern, introduced parcel-level spatial resolution, demonstrated the possibility of rapid development and deployment, and used innovative techniques for rapid equilibration of AB model systems.

The Lake Tahoe project was the first implementation for a small Local Authority, and the first to transfer and recalibrate a model built for another region (MORPC).

The Oregon model was the first AB model to be implemented for an entire state, and it was also integrated into a land use model system.

Ohio imported the Oregon statewide model and enhanced it to include long distance inter-regional trips.

The Atlanta model, which will be based on the MORPC design, hasn't been fully implemented yet, but they have implemented a flexible population synthesizer, and the design includes other innovations.

DRCOG, MTC and PSRC are the most recent locations where new development projects are under way. PSRC is the first staged implementation in which the first stage involves integrating a day activity pattern model with the existing trip-based model system.

A Comparative Summary of Features

This section provides a concise summary of important design features of various AB model systems that have been implemented or have recently been designed for planning agencies in the U.S. The models described are those mentioned in the previous section, with a few exceptions. Lake Tahoe is excluded because it is essentially a clone of MORPC, and Oregon and Ohio are excluded because they are statewide models. A model for Dallas (CEMDAP) is included because, although no agency has expressed a commitment to use it, it is in an advanced state of development. We have also excluded the FAMOS model for Tampa Bay, which is still primarily a laboratory project, and the TranSIMS model, for which the AB component is not well developed. Finally, we have included the PSRC model system with the Activity Generator incorporated, even though it remains in part a trip-based model system, because it represents one way of transitioning from a trip-based model.

Except for the PSRC model system, all of the model systems described in this section are similar in several important aspects:

- represent an entire day of activities and travel for each member of a synthetic population, using stochastic microsimulation
- consist of an integrated system of econometric models

- include traditional traffic and public transport assignment components

In addition, the integrated econometric model systems are similar in overall structure, with a hierarchy of levels from “top” to “bottom”, where lower level choice predictions are conditioned by those at higher levels, and higher level choices are influenced by accessibility measures that capture the effect of choice opportunities occurring at lower levels. The levels are:

- Population synthesis (geographic allocation of households)
- Longer term decisions: auto ownership and (in some cases) work and school locations
- Person/household-day level: choices that span the entire day for one or more persons in the household
- Tour-level: The main destination, travel mode, begin and end times, and number of stops for each tour
- Trip-level: Intermediate stop location, and the mode and departure time of each trip

Within this structure, there are several important design features and other aspects that distinguish the models, and these are summarized in Table 1 below. At the time of this writing, the Bay Area (MTC) and Denver (DRCOG) models are in the development stage, and the San Francisco model is undergoing a major upgrade, so the design characteristics shown for those models may be in a state of flux. Each paragraph below is a more detailed annotation of a row in the comparison table.

Implementation status: The Metro model was implemented and used once without complete calibration, and subsequently not used. Four of the models, San Francisco (SFCTA), Sacramento (SACOG), New York (NYMTC) and Columbus (MORPC) are in ongoing use, with ongoing maintenance and improvement. The Dallas model (CEMDAP) has been implemented for validation purposes in a laboratory setting. The remaining models are in various stages of development.

Controls/categories for population synthesis: All of the model systems simulate persons one by one, and require a representative sample of households and persons for the base year and forecast years. All of the regions use zone-level data and forecasts of household size and income as control variables for sampling households from the regional PUMS households. In addition, most of the regions have used the number of workers in the household as a third control variable, both because it is important behaviorally, and because a census table (CTPP Table 1-75) provides a useful 3-way joint distribution of household size, number of workers and income for 2000. The Portland (METRO) and San Francisco (SFCTA) models have also used age of head of household as a control variable, and Atlanta (ARC), Bay Area and Denver are all considering using age or age-related variables as well (e.g. presence of children and/or senior citizens). San Francisco (SFCTA) is also using controls for presence of children, single vs multi-family dwelling, race/ethnicity, and is explicitly synthesizing residents of group quarters housing. The sample generation software created for Atlanta has a flexible system for designating and combining control variables, as well as facilities for testing how well the synthetic population matches other variables that have not been explicitly controlled.

SFCTA, MTC, DRCOG, MTC and PSRC are all using derivatives of the ARC population synthesizer.

“Usual” work & school locations modeled at the top level: There is a recognition that the choice of where to work and where to go to school are longer-term decisions that are not adjusted day to day, similar to the choice of residence (which is implicitly modeled in the synthetic sample). In most of the models, and all of the more recent ones, the “usual” work and school places are modeled at the “top” level, meaning that these are predicted before predicting any choices specific to the travel day. The home location is typically one of the alternatives in the choice set, for people whose main workplace is at home or who are home-schooled. Note that certain types of individuals such as construction workers or traveling salespeople may not have a “usual” workplace. Also note that this model formulation requires that data be collected on each worker’s most frequent work location, even if that person does not visit that location on the survey diary day(s). The destination for any particular work tour will most often be the “usual” work location, but may be another location instead (a business meeting, for example), and that choice is modeled accordingly at the tour level. School tours nearly always go to the usual school location, so school location should be modeled as a long-term choice and a separate school tour destination model may not be needed. In the future, it would be ideal for the population synthesis and longer term models to be replaced by a dynamic, integrated land use model that includes joint prediction of residential and workplace (re)location decisions.

Number of out-of-home activity purposes: The simplest purpose segmentations are in the San Francisco model, with 3 purposes (work, school, other). Most other model systems have included at least 7 activity purposes, being work, school, escort (serve passenger), shopping, meals, personal business (or “other maintenance”), and social/recreation (or “other discretionary”). In some cases, social visit has been separated from recreation. The main reasons for splitting out the meal activity are that it tends to be done at certain types of locations, and has very specific time-of-day and duration characteristics. The escort activity also tends to be to specific locations at specific times in terms of driving children to and from school. Note that in tour-based models we do not need to treat non-home-trips as if they are separate “purposes”, although all of the systems do have separate tour level models for work-based tours (often called “subtours” because they are tours within tours). In most of the model systems, the division of the school purpose into university, K-12 and pre-school is made in the lower level models based on the age and enrolment type of the particular person in the sample.

Number of in-home activity purposes: In the Portland model, in-home activities are distinguished between 3 purposes (work/school, maintenance and discretionary), but this distinction is only made for the “primary” activity of the day, and is only predicted in cases when the person has no out-of-home activities. None of the other models distinguish between types of in-home activities. Some of the models predict which people work primarily at home, providing some substitution between in-home and out-of-home work. They do not, however, handle the phenomenon of part-time telecommuting, which is the focus of some demand management policies. As a result, there is some interest in predicting work-at-home as a separate activity type in the Bay Area model if the data will support it.

Day pattern type linked explicitly across HH members: All of the models treat linkages across household members implicitly through the use of a wide variety of person type and household composition variables. However, some of them have begun to use explicit linkages between the predicted activities and travel of different members of the same household, which makes microsimulated activity and travel itineraries more consistent among household members. This and the following three paragraphs are concerned with the modeling of these explicit linkages. One of the key linkages is a fairly simple one. If each person's full day activity pattern is classified into three main types—stay at home, go to work/school, or travel for some other purpose—then we see strong similarities between the patterns of members of the same household. The Columbus model system includes a sequential model of these linkages, simulating children first, and then adults conditional on what the children do. The Atlanta model system includes a similar model that is estimated simultaneously across all household members, avoiding the need to assume the order in which they are simulated and thus the direction of causality. A similar model is planned for the Bay Area system.

Joint activities linked explicitly across HH members: Joint activities are cases in which two or more household members travel together to and from an activity location, and participate in the same activity while at that location. In the lower level models such as mode and destination choice, it is best to model such cases as a single joint decision, rather than as independent decisions made by different people. The Columbus and Atlanta model systems include models of household joint activity generation and participation. The application of the Columbus model has shown that predicting joint travel can have significant implications for mode choice, so this type of model has been recommended for the Bay Area model. However, in a wider sense the "jury is still out" as to what extent the additional accuracy of explicitly modeling household interactions will merit the additional complexity. For that reason, such models will not be included in the Denver system, at least in the initial version.

"Escort" trips linked explicitly across HH members: Another type of joint travel is the case where two or more household members travel together to and/or from an activity location, but do not participate in the same activity there. The most common example is a parent driving a child to school and then either returning home (an escort tour) or else driving on to work (an escort stop on a work tour). Because these types of tours are partly joint and partly independent, it can be very complex to explicitly link them across persons. For that reason, explicit modeling of escort linkages has not been done in any of the applied models or recommended for the models under design. Most of the models, however, do include a separate "escort" purpose, so that the most important special characteristics can be captured—particularly the fact that the mode is nearly always auto, with the exception of infrequent cases of walk escort. Also, children's school locations can easily be included as special alternatives in the parents' escort tour destination choice sets, so that at least the location is accurate, even if the exact trip timing and car occupancy are not matched.

Allocated activities divided explicitly among HH members: Certain types of activities such as grocery shopping, escorting, and some other "maintenance" chores, are likely to be allocated across individuals in a household, showing a negative correlation of frequencies and duration across household members within a household-day. The Columbus and Atlanta model systems assume that activities for certain purposes are conducted on behalf of the household, and include explicit models of the generation of these activities at the household level and then allocation to particular individuals. In the Atlanta case, this model was estimated jointly with the household joint travel generation model. Compared to explicitly linking people who make joint tours together, predicting which people within a household perform allocated activities appears less important to the model results—we are not changing anything fundamental about the tours, just which person makes them. So, these models seem less crucial than the joint travel models. In addition, it is difficult to reliably determine, from existing surveys, which activities are most likely to be allocated. For example, grocery shopping is mainly an allocated activity, while shopping for a good book to read is an individual activity, but both are usually coded the same. So, without better survey data designed to distinguish activities by whether they achieve household or personal objectives, the quality of models that attempt to allocate household activities is questionable.

Level at which intermediate stop purpose and frequency are modeled: When ordering the models in an AB system from "top" to "bottom", it is not always clear which decisions should be modeled conditional on which other decisions. A prime example is the generation of intermediate stops made during tours. Are activities planned and combined into trip chains when a person is planning their day, in which case the mode, timing and location of the tours may depend on which stops they contain? Or, conversely, do people make tours, and then decide during the tour how often and where to make stops depending on their mode and location? Clearly, both of these describe real behavior, and which description is more accurate depends on the particular person and the types of activities they are carrying out. The Portland and San Francisco models follow closely the original Bowman and Ben-Akiva day pattern approach, in which the presence (and, in the case of Portland, basic purpose) of intermediate stops are predicted at the person-day level. In contrast, the Columbus, New York and Atlanta models predict only the number and purpose of tours at the person-day level, and then the presence, number and purpose of intermediate stops on any particular tour are predicted at the tour level once the tour destination, time of day and main mode are known. In the Sacramento models, another approach is used. Some information about stop-making is predicted at the person-day level, predicting whether or not any intermediate stops are made for each activity purpose during the day (7 yes/no variables). These are predicted jointly with the choice of whether or not to make any tours for each of the activity purposes (7 more yes/no variables), thus capturing some substitution effects between the number of tours and the number of trips per tour. Then, when each tour is simulated, the exact number and purpose of stops on each tour are predicted conditional on the mode and destination of that tour and conditional on what types of stops still need to be simulated to fulfill the person-day level prediction. There is no proven behavioral reason for this structure, but it “balances” the model sensitivities between the two types of behavior described above. A similar approach is being used for Denver and PSRC.

Number of network zones used: This and the next two paragraphs discuss spatial aspects of the model systems. In all cases, the zone system used for model development and application is the same as was also used for trip-based models. The auto and public transport networks and assignments are also the same as used in the trip-based models. This fact has facilitated the transition to AB models, but at the same time, the travel decision microsimulation framework can also be used with more detailed spatial systems, and would support more accurate traffic simulation methods as well.

Smaller spatial units used below zones: Because the travel decision microsimulation framework is not tied strongly to zone definitions, it is possible to use the zones only to provide the road and public transport path level of service variables, while variables related to land use, parking, and walk access (which do not need to be stored as matrices) can be specified at a finer level. The Portland model uses such an approach for roughly 20,000 “block faces”, while the Sacramento models use over 700,000 parcels. In both of these model systems, this fine level of disaggregation is used to define the destination choice alternatives and their attractiveness, to provide detailed mode choice information at the trip-ends related to accessibility of public transport, and level-of-service for non-motorized modes and intra-zonal trips. Denver is going to use “utility hookup points” instead of parcels, but primarily for modeling mode choice. With these two-level systems, the importance of very small traffic assignment zones is lessened. But the size of zones still needs to be small enough to achieve homogeneity of travel times and costs for the motorized portion of inter-zonal trips, as well as the availability and nature of public transport and highway access points.

Simultaneous mode and destination choice model estimation: It has become a sort of tradition in modeling to condition mode choice upon a known destination, sometimes using a sequential nested structure where the mode choice logsum is used in the destination choice model. That is probably appropriate for purposes such as work and school. For purposes such as shopping, however, the choice of store may sometimes depend more upon the mode used than vice-versa. Simultaneous estimation of mode and destination choice allows the modeler to test different nesting hypotheses. Such an approach was used in the Portland model, but has not been use since by any of the implemented model systems.

Modelled time periods and time-constrained scheduling: Most 4-step models only use two times of day—peak and off-peak, and use fixed time-of-day factors. All of the AB models contain tour time of day models that allow some sensitivity of time of day choice to network conditions. All of the models have used at least 4 highway assignment periods—AM peak, midday, PM peak and off-peak. In some cases, free flow conditions are assumed for off-peak, so no traffic assignment is needed for that period. In some models, a fifth period has been added by splitting the off-peak period into early morning and evening/night. The more recent models, beginning with Columbus, use more precise time windows in order to schedule each tour and trip consistently during the day. This involves keeping track of the available time windows remaining after "blocking out" the time taken by each activity and associated travel. The time windows can also be used in the activity generation models. The Sacramento model and perhaps other models are moving to half-hour periods to provide even more detail. The main constraint on how small the time periods can be is the adequacy of the self-reported times in the diary survey data. There is evidence that people often round clock times to 10, 15 or 30-minute intervals. The effectiveness of modeling time at a detailed level is hampered by the use of no more than four or five time periods for traffic assignment, increasing the pressure to use more time periods for traffic assignment, and to move to dynamic traffic assignment. Denver is implementing 8 assignment time periods, and SFCTA and PSRC have implemented an assignment procedure that takes the equilibrated results of two 3-hour peak period assignments and generates differentiated level-of-service skims for each half hour within the peak.

Tour time of day relative to mode and destination choice models: It is not obvious whether activity and departure times should be predicted before mode and destination choice, between them, or after both. There is some empirical evidence that shifts in time of day occur at two levels: the choice among broad periods of the day (e.g. morning, afternoon, etc.) is made fairly independently of accessibility, while smaller shifts of up to an hour or two are more sensitive to travel times and costs—the peak-spreading effect. Since all of the models use broad network time periods, the tendency has been to model the choice of these periods for tours at a fairly high level above mode and destination choice (although in most cases the usual destination for work and school tours has already been predicted). In some models, time of day choice is predicted between the destination and mode choice levels, which allows the use of destination-specific mode choice logsums in the time of day model, but requires that the destination choice model assume (or stochastically select) a specific time of day for the impedance variables. SACOG models time of day below destination and mode. For DRCOG, the data support modeling tour TOD above mode choice for work and school tours, but below mode choice for other tour purposes.

Departure time choice modeled separately at the trip level: Perhaps the placement of the model that predicts the choice of times for the overall tour is not as crucial if there is a separate model that predicts the departure time for each trip to the more detailed periods, conditional on the mode, origin and destination of each trip. Some of the model systems include such a model as the "lowest" model in the system. It is also possible to include such a model for car trips only, in order to predict the shape of the demand profile within the broader peak periods.

Accessibility measures in the upper level models: The issue of how to include accessibility and land use effects in the upper level models is extremely important, because it determines the accuracy with which the models represent sensitivity of activity, tour and trip generation and patterns to transport level of service and the distribution of activity attractions. Calculation of full logsums across all possible nests of lower level alternatives is infeasible with so many levels of choices. The earliest Portland models came the closest to including "proper" individual-specific logsums, but the structure of that model was relatively simple, and the effect on model run-time was severe. Initially, the San Francisco model included mode-specific measures with set boundaries, such as the number of jobs accessible within 30 minutes by public transport. The rather arbitrary cutoff boundaries in such measures can cause unexpected sensitivities when applying the models. It has recently been enhanced to use logsum-based accessibility measures. The New York and Columbus models use mode-specific travel time decay functions that approximate the logsum from a simple destination choice model. Such measures perform better, but still have the problem that they are mode-specific, and that auto and public transport accessibility tend to be correlated, so it is difficult to estimate model parameters for both of them. A method that solves this problem and is more consistent with discrete choice theory is to approximate joint mode/destination choice logsums. However, the mode choice logsums tend to vary widely across the population, so it is best to calculate different accessibility measures for different population segments. The Sacramento models use such an approach, with aggregate accessibility logsums for each combination of 7 travel purposes, 4 car availability segments, and 3 walk-to-public transport access segments—as those tend to be the most important segmentation variables in the mode choice models. Both DRCOG and PSRC are using aggregate accessibility logsums similar to those used by SACOG.

Conclusion

Since the early 1970s, when the basic concepts of activity-based travel were articulated, there has been an ongoing effort by a host of contributors to enhance our understanding of the behavioural framework, empirically test the theories, and implement them in practical travel demand models used for planning and policy. These models have progressed from disaggregate trip-based models, to models representing tours, and now to full day activity and travel schedules. Practical model systems now microsimulate full day itineraries for synthetic populations of entire metropolitan regions, representing the influence of real-world constraints and influences with increasing realism. We expect that the realism of activity-based travel decision microsimulation models will continue to improve, that activity-based demand models will be integrated with highway and public transport microsimulation models, and that the usage of these models for practical planning and policy analysis will become more widespread in the years ahead.

Table 1: Features of Various Activity-Based Model Systems

Feature	Portland Metro	San Francisco SFCTA	Sacramento SACOG	Denver DRCOG	Seattle PSRC with Activity Generator	New York NYMTC	Columbus MORPC	Atlanta ARC	Bay Area MTC	Dallas (CEMDAP)
Implementation Status	Discontinued	In use	In use	Development	Development	In Use	In Use	Development	Development	Laboratory
Controls / # categories for population synthesis	4 hh size 4 income 4 age	4 hh size 3 # workers 4 income age, children	4 hh size 4 # workers 4 income	4 hhsize, 3 # wkrs, 4 inc, #adlts, kids, 3 holder age	similar to ARC	5 hh size 4 # workers 4 income	5 hh size 4 # workers 4 income	100+ comb. of hh size, # wkrs, inc, age, children	4 hh size 4 # workers 4 income Age (?)	
Population synthesizer	Custom	ARC PopSyn	Custom	ARC PopSyn	ARC PopSyn (base year)	Custom	Custom	ARC PopSyn	ARC PopSyn	UT CEMDAP
"Usual" work & school locations at top level?	Yes	Yes	Yes	Yes	Work	No	No	Yes	Yes	Yes
Number of out-of-home activity purposes	8	3	7	7	7	4	7	8	7 or 8	11 for adults 3 for children
Number of in-home activity purposes	3	1	1	1	1	1	1	1	1 or 2	1
Day pattern type linked explicitly across HH?	No	No	No	No	No	No	Sequential	Simultaneous	Simultaneous	Sequential
Joint intra-HH activities?	No	No	No	No	No	No	Yes	Yes	Yes	Parent & child
Linked intra-HH "escort" trips?	No	No	No	No	No	No	No	No	No	Yes
Allocated HH activities?	No	No	No	No	No	No	Yes	Yes	No	Yes
Level where stop purpose and frequency are modeled	Person-day	Person-day	Person-day and tour	Person-day and tour	Person-day and tour	Tour	Tour	Tour	Person-day and tour	Person-day and tour
Network assignment zones	1,250	2,336	1,300	2,800	938	6,000	2,000	2,500	1,600	
Smaller spatial units used?	20K blocks	No	700K parcels	Points for mode choice transit access	No (parcels in next version of models)	No	No	No	No	
Mode and destination model estimation	Simultaneous	Sequential	Sequential	Sequential	Sequential trip-based	Sequential	Sequential	Sequential	Sequential	
Network time periods	5 per day	5 per day (12 ½hr peak subperiods)	4 per day	8 per day	5 per day (12 ½hr peak subperiods)	4 per day	5 per day	4 per day	5 per day	
Modeled time periods	5 per day	30 min (new)	30 min	30 min	30 min	4 per day	1 hour	1 hour	30 min	
Scheduling constrained by available time windows?	No	No	Yes	Yes	No	No	Yes	Yes	Yes	
Tour time of day relative to mode and destination	Above	Above	Below	Above for non-work	Below	Between	Between	Between	Between	
Departure time modeled separately at trip level?	No	Yes (auto peak trips)	Yes, lowest model	Yes, lowest model	Yes (auto peak trips)	No	No	Yes, lowest model	Yes, lowest model	
Accessibility measures in upper level models	Person-specific mode / dest logsums	Jobs reached by zone/ mode/time band,logsums	Mode & dest logsums by zone / segment	Mode & dest logsums by zone / segment	Mode & dest logsums by zone / segment	Dest choice logsums by zone / mode / segment	Dest choice logsums by zone / mode / segment	Dest choice logsums by zone / mode / segment	Mode & dest logsums by zone / segment	

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