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An assessment of activity-based modeling and simulation for applications in operational studies, disaster preparedness, and homeland security

ABSTRACT: In order to discuss features needed for homeland security modeling, a review of behavioral model paradigms and their application in travel and wayfinding along with the review of 53 activity-based models have been conducted. Two examples of homeland security studies are included to highlight these needs. This review demonstrates that only a few of the models have the desired characteristics of fine spatial and temporal resolutions as well as explicit cognitive-behavioral capabilities. Because the criticality of locations varies due to time and/or the day of the week depending on the presence of individuals and the fact that potential targets are specific locations within a city, data needs for modeling these types of scenarios exceed typical planning and forecasting modeling as well as research modeling. Finally, a discussion of data and information gaps in current research is included that focuses on land use and population data shortfalls, the need incorporating more time constraints in activity modeling including weekly and seasonal variations in travel behavior, developing a new paradigm for activity scheduling in panic and emergency situations, and the need to understand behavioral errors and biases.

KEYWORDS: Homeland security, emergency management, activity-based model, simulation

INTRODUCTION

In this paper, we examine the plethora of activity-based approaches as candidates for operational studies, disaster preparedness, and homeland security applications. These methods contain by design some of the most attractive features available because they could be used to predict the presence of a city's population at specific locations and at explicitly defined times of a day. Our assessment aims at identifying key features of homeland security applications, conducting a review of existing activity analysis methods and their fundamental building blocks, and providing a broad brush identification of gaps to build repeatedly running homeland security applications.

According to Ettema and Timmermans (1997), "activity-based approaches typically describe which activities people pursue, at what locations, at what times and how these activities are scheduled, given the locations and attributes of destinations, the state of the transportation network, aspects of the institutional context, and their personal and household characteristics." Activity-based models have been developed to create activity patterns that more accurately reflect how people plan and organize their days. This is important so policy changes can be evaluated to determine how these will affect transportation networks. Although the behavioral, temporal and spatial resolutions utilized by the numerous models developed in the past 25 years vary greatly, these may be adequate depending on the policy application at hand. However, when these models are viewed though a filter of homeland security application requirements, only a handful of the models have been built on a suitable cognitive basis along with either the time and/or space resolution to reasonably provide useful results.

As with using activity-based modeling to evaluate policy changes, applying the same models to homeland security problems requires more sensitivity that can be obtained

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via the typical four-step model available in most large Metropolitan Planning Organizations (MPOs). In fact, due to transportation policy considerations, many of the larger MPOs are moving away from tradition methods and towards activity-based approaches for use in travel demand management and transportation system management policies. However, we believe that the majority of the activity-based models may not be able to sufficiently answer homeland security questions without further work to increase the cognitive-behavioral richness underlying the models and improve the current time and location resolutions being utilized. As examples, we use two homeland security studies that highlight this inadequacy. Improvements in spatial and temporal resolution, specifying explicit cognitive-behavioral capabilities, reliability of land use and population information, and improving activity schedule creation by including time constraints and better understanding of inter- and intra-household interactions seem to be the most important improvements required.

The next section provides an overview of the needs for homeland security applications with examples. Immediately after that we offer an overview of behavioral model paradigms and cognitive behavioral approaches setting the background for a more detailed review of a sample of activity-based models. Then, specific gaps left by all these models are described and the paper concludes with a summary.

HOMELAND SECURITY AND TRANSPORTATION MODELING

Homeland security applications aim at developing scenarios of events, consequences, and strategies to minimize the impacts of consequences. Minimization of the consequences, however, requires that we also account for limited resources and rely on cooperation from a variety of individuals and groups. As a result, developing homeland security modeling applications involve questions that must be addressed because they vary from typical transportation models. For example:

- What is the purpose of the model?
- Will a scenario be written and executed?
- For scenarios, how detailed do they need to be?
- How large of an area will be included in the model?
- How detailed do the models need to be?
- Who plays what role and under what circumstances?
- What are some typical behaviors we should expect and how do we handle them?

On July 15, 1996, President Clinton signed Executive Order 13010 establishing the President's Commission on Critical Infrastructure. The Commission's mandate was to develop a national strategy for protecting the country's critical infrastructures from numerous types of potential threats and assuring their continued operation. This council recommended that complex subjects, including the nation's transportation system, undergo threat and risk assessments (GAO, 1998). President George W. Bush released Homeland Security Presidential Directive- 7 (HSPD-7) on December 17, 2003, to establish "a national policy for Federal departments and agencies to identify and prioritize United States critical infrastructure and key resources and to protect them from terrorist attacks." (Office of the Press Secretary, 2003) According to the Government Accountability Office (GAO, 2005) in testimony given on February 15, 2005 before the Committee on Commerce, Science, and Transportation in the United States Senate, the Transportation Security Administration (TSA), which is responsible for the security of all modes of transportation as outlined in the Aviation and Transportation Security Act (ATSA) (Pub. L. No. 107-71), needs to implement a risk management approach for prioritizing efforts and focusing resources. This includes conducting criticality assessments to evaluate and prioritize assets and functions in terms of specific criteria, such as a structure's significance as a target, the importance of it to accomplish a mission, and the ability and potential cost to repair or replace this capability, as a basis for identifying which structures or processes are relatively more important to protect from attack. For example, key bridges might be identified as "critical" in terms of their importance to national security, economic activity, and public safety. Or, large sports stadiums, shopping malls, and office towers might be considered more of a substantial target when they are in use, but not when they are empty. Criticality assessments would provide information needed to determine which structures and assets are most important to protect from an attack and need to have resources allocated for special protective actions (GAO, 2001).

The key aspects emerging from this are: a) criticality of each location changes with time of day and/or day of the week depending on the presence of persons in and around the location; and b) potential targets are specific and distinct locations that are major attractors of activity. Both aspects require fine modeling and simulation resolution in time and space in combination with suitable behavioral principles to represent travel behavior. To illustrate this, two examples of different types of disaster preparedness are described.

Topoff 3:

Top Officials 3 (TOPOFF 3), conducted in 2005, with a full-scale exercise occurring on April 4-8, 2005, was the largest and most comprehensive terrorism response exercise ever completed in the United States to date. This Congressionally-mandated national terror exercise was conducted by federal, state, local, tribal and private sector organizations as well as the United Kingdom and Canada. The $16 million event, which took two years to plan, involved simulating a chemical and a biological incident. In New London, Connecticut, a fictitious car bomb exploded on a crowed pier sending deadly mustard gas out into the air, while in Union, New Jersey, an abandoned sports utility vehicle (SUV) was found rigged with an atomizer. Although no traces of biological agents were found near the SUV, patients began overwhelming area hospitals as they developed flu-like symptoms. (Kime, 2005)

FHWA Disaster Scenarios:

In 2003, a study completed for the Federal Highway Administration (FHWA) analyzes four different catastrophic events. These include the terror attacks in New York City and Washington, D. C., on September 11, 2001, the Northridge, California earthquake on January 18, 1994, and the Baltimore, Maryland Howard Street rail tunnel fire on July 18, 2001. The immediate and long-term impacts on each city's local and regional transportation systems are examined. Two of the documented lessons learned are important for our purposes: (a) an agency needs to learn from previous events and incorporate learning into an agency's response plans; (b) the need to practice for the expected and the unexpected. The report also noted that in each of the emergencies, transportation agencies had to work together to provide alternate travel options to the public and that these alternatives shifted over time in response to changes in travel behaviors of the public (DeBlasio, et al, 2003).

To implement these types of scenarios, sets of highly detailed information must be generated. Depending on the time of day to be modeled, the population will have to be given home, work, and other locations to perform activities such as grocery shopping, attend school, or visiting the dentist. If the event is either a chemical and biological attack, the locations of the initial releases in the scenario must be predefined. While these are both point locations, their areas of influence, decreasing in strength as you move away from the impact location, must be overlaid onto the network. From this, you can see who in the population will be affected. At this point, travel restrictions can be imposed on the network. As with any emergency, first responders will want the danger area cordoned off so that people involved in the incident can be helped and any crime scene information needs to be minimally impacted. Also, with this type of incident, the need to minimize contact between uncontaminated persons and biological or chemical agent (bc-agent) is required. Victims who come in contact with a bc-agent need to be directed to decontamination areas. These efforts will require parts of a city to be closed off from the transportation network. Other bystanders, if needed to be evacuated, must leave the area while no longer being able to use certain local and arterial streets. The locations of network routes must also be modeled. For example, the Twin Towers destroyed in the September 11, 2001 bombing had a subway station located directly beneath them. Knowing approximately where on the network transit vehicles were expected to have been traveling is very important in estimating the number of people who may be affected by radiation or a chemical or biological release when traveling through a contamination plume before a release is discovered.

To truly prepare for the unexpected by running scenarios of terrorist attacks or ranking assets to determine more sensitive areas, activity models that do not operate at fine levels of spatial and temporal detail may be too coarse to gain any insight and practice for the unexpected. For example, if a dirty bomb were released at a sport stadium or on an elevated train station, how would this be simulated at a traffic analysis zone (TAZ) level? How would you define a contamination zone? Depending on the size of an incident, these become important questions. For terrorist events, the ability to model areas down to the parcel location might be more important than when modeling natural disasters. For example, the scenario outlined in TOPOFF 3 simulated both a chemical and a biological incident. The original release locations would be single points. Based on this, the resulting plume clouds can be modeled using an atmospheric model and overlaid on top of an activity-based transportation model. Individuals passing through the cloud can be tagged and their locations monitored as they travel through the city. If the biological agent was spread through contact, it would be possible to extrapolate how the disease spreads through individuals coming in contact with one another at activity locations (work, home, shopping locations, etc.). This type of modeling at such fine detail would not be possible if the activity locations were limited to TAZ centroids. Using this same example, how would you model the evacuation of areas that are threatened by a plume when time is critical, especially if the only lowest available time unit is a 3-hour block? In three hours, depending on wind speed, a plume cloud can expand quickly and begin to dissipate. It would be difficult to estimate which portion of the population received the largest dosage exposure. Finally, it is imperative that the simulated population's travel behavior reflects that of reality as much as possible. The value of utilizing an activity-based model and having people undertake trips, either alone or with other people, use mass transit or going alone in a car for various trip purposes is important in determining where the population actually is at any one time during the day. If an agency is to practice for the unexpected and incorporate lessons learned into response plans as highlighted by the FHWA, a different sort of strategy is needed to conduct homeland security-related exercises. A variety of innovations in travel demand modeling and simulation coupled with advances in cognitive behavioral transportation approaches may offer new options for homeland security models.

MODELING TRAVEL BEHAVIOR

Activity and travel behavior is mostly concerned with persons and their social units from which motivations for and constraints to their behavior emerge. Observed behavior is the outcome of a process. Conceptual models of this process are transformed into computerized models of an area that utilize components of human judgment and decision making models, such as travelers moving around the transportation network and visiting locations where they can participate in activities. Models of this behavior are simplified versions of strategies used by travelers to select among options that are directly related to their desired activities. In some of these models, assumptions are also made about hierarchies of motivations, actions, consequences, learning, and interactions with people and the environment. Some of these assumptions are explicit, e.g., when deriving the functional forms of models as in the typical disaggregate choice models; in other models these assumptions are implicit, such as in models of individuals that assume no interaction with other people takes place. Below is a summary of prototypical paradigms that form the basis of operational activity-based models. Following this is a discussion of the roles memory and spatial cognition have in modeling people's movements through their environment.

Behavioral Paradigms

Rational decision making is a label associated with human behavior that follows a strategy to identify the best course of action by solving an optimization problem. When an operational model is required to provide quantitative predictions about human behavior, some kind of mathematical apparatus is needed. One such machinery is the subjective expected utility (SEU) (Savage, 1954) formulation of human behavior. In developing alternative models to SEU, Simon (1983) defines four theoretical components for SEU:

a) a person's decision is based on a utility function assigning a numerical value to each option — *existence and consideration of a cardinal utility function;*
b) the person defines an exhaustive set of alternative strategies among which just one will be selected — *ability to enumerate all strategies and their consequences;*
c) the person can build a probability distribution of all possible events and outcome for each alternate option — *infinite computational ability;* and
d) the person selects the alternative that has the maximum utility — *maximizing utility behavior*.

This behavioral paradigm served as the basis for a rich production of models in transportation-related choice analysis that includes the mode of travel, destinations to visit, and the household residence (see examples in Ben-Akiva and Lerman, 1985). It served also as the theoretical framework for consumer choice models and for attempts to develop models for hypothetical situations (Louviere, *et al*, 2000). Finally, it has also replaced the aggregate modeling approaches to travel demand analysis as the orthodoxy against which many old and new theories and applications are compared and compete with.

SEU can be considered apart of a larger family of weighted additive rule (WADD) models (Payne, *et al*, 1993). Real humans, however, may never behave according to SEU or related maximizing and infinitely computational capability models (Simon labels this the Olympian model, 1983). Based on this argument, different researchers in psychology have proposed a variety of decision making strategies (or heuristics). For example, Simon created alternate model paradigms under the label of *bounded rationality — the limited extent to which rational calculation can direct human behavior* (Simon, 1983, 1997) to depict a sequence of a person's actions when searching for a suitable alternative. The modeled human is allowed to make mistakes in this search providing a more realistic description of observed behavior (Rubinstein, 1998). Tversky is credited with another stream of decision-making models starting with the *lexicographic approach* (1969), in which *a person first identifies the most important attribute, compares all alternatives to the value of this attribute, and chooses the alternative with the best value.* Ties are resolved in a hierarchical system of attributes. Another Tversky model (1972) assumes a person selects an attribute in a probabilistic way; all alternatives that do not meet a minimum criterion value (cutoff point) are eliminated. The process is repeated until just one alternative remains. This has been named the *elimination by aspects strategies* (EBA) model. Later, Kahneman and Tversky (1979) developed *prospect theory* which evolved into the *cumulative prospect theory* (Tversky and Kahneman, 1992). After an initial simplification step, a value is assigned to each outcome and a *decision is made based on the sum of values multiplying each by a decision weight*. Losses and gains are treated differently.

All these alternatives to SEU paradigms did not go unnoticed in transportation research — early significant applications began appearing in the late 1980s. In fact, a conference was organized attracting a few of the most notable research contributors to summarize the state of the art in behavior paradigms (Gärling, *et al*, 1998). One of the earlier examples using another of Simon's inventions, the *satisficing behavior — acceptance of viable choices that may not be optimal* — is a series of transportation-specific applications described in Mahmassani and Herman (1990). Subsequent contributions continue along the path of more realistic models. The most recent example by Avineri and Prashker (2003) uses cumulative prospect theory. However, as Gärling, *et al* (1997) and Avineri and Prashker (2003) point out, these paradigms are not ready for practical applications, contrary to efforts by Mahmassani and colleagues. Additional work is required to use them in a simulation framework for applications. In addition, Payne, *et al* (1993) provide an excellent review of these models and a summary of the differentiating aspects among the paradigms. Most importantly, they provide evidence that decision makers *adapt* (switch between decision-making paradigms) *to the task and the context of their choices*. They also make mistakes and may also fail to switch strategies. As Vause (1997) discusses in some length, transportation applications are possible using multiple decision-making heuristics within the same general framework and employing a production system approach (Newell and Simon, 1972). Adaptation may be very different depending on the context of decision making. In the context of homeland security applications, considerable time pressure and fear may trigger completely different behavioral mechanisms than normally utilized in everyday commuting.

However, this key consideration has received little attention in transportation. Recent production systems (Arentze and Timmermans, 2000) are significant improvements over past simulation techniques. Even within this broader and richer theoretical framework, travelers are still assumed to be passive in shaping the environment within which they decide to act (action space). This action space is viewed as largely made by constraints and not by their active shaping of their context. In contrast, Goulias (2001, 2003) reviews another framework from human development that is designed to treat decision makers in their active and passive roles and explicitly accounts for mutual influence between an agent (active autonomous decision maker) and her environment. This framework was never used in a complete application. One way to represent context is to use ideas from spatial cognition and what many researchers know as mental or cognitive maps. Most important, however, is also the recognition of the role short and long term memory play in spatial cognition for modeling the movement of people in geographic space.

Wayfinding

While navigation is usually described as a process of following a pre-defined path through a complex environment to a specified destination, wayfinding is a more general term used to describe travel behavior that is more search-oriented and less inclined to be optimal. Wayfinding can take place in both familiar and unfamiliar environments. In a familiar environment, the traveler might explore alternate paths to a destination in the presence of congestion, accidents, or other intervening obstacles that are found in the path specified by a travel plan. Since most people do not use maps for their everyday travel, they rely on a wayfinding process that is dependent both on information stored in long term memory and on one's recall abilities. These memory structures, or cognitive maps, comprise the data brought into working memory to help the traveler make decisions at critical choice points along a path. However, the mental maps vary considerably in accuracy and reliability. In well known parts of the city (e.g., those parts experienced on regular, episodic work trips), one's cognitive map may be very accurate in that it closely reflects objective reality. In more distant or nonfamiliar, the cognitive map might be quite distorted (fuzzy) and incomplete.

Two sources are generally acknowledged as being critical in spatial cognition. The first, perception-action systems (Creem and Proffitt, 1998; Allen and Haun, 2004), describes a set of sensory motor systems that provide very accurate time and context sensitive memory for spaces. It is primarily based on sensory motor mechanisms (visual, auditory, kinesthetic, and vestibular), and is not mediated by any memory representation. Therefore, the environment is not constantly monitored and actions occur largely without thinking, such as when walking down stairs. Allen and Haun (2004) suggest a second source of information contained in one's cognitive map. This consists of an accumulated knowledge base for general use when performing episodic activities. It requires attention and effort, both in terms of coding and decoding or retrieval. Essentially, it is experiential. For example, Allen (1981) suggested that route learning is done using a system called "chunking" — dividing routes into blocks that are learned and linked sequentially.

Travel in urban environments depends upon the nature of acquired knowledge. This includes the ability to recognize and recall specific places (e.g., nodes, landmarks). This is generally known as declarative knowledge, or more specifically as landmark knowledge (Siegel and White, 1975). Landmark knowledge implies specific identification of place. When traveling, this declarative knowledge base is analyzed according to procedural rules ("if-then"). The ability to link places together to form routes or trajectories is called route knowledge. When individual routes are integrated, a system-type awareness of an environment emerges and is called survey or configurational knowledge. While route knowledge is essentially sequential, survey or configurational knowledge is layout-based and is at least two-dimensional. Landmark knowledge consists of knowledge of points or places; route knowledge consists of ordinal mapping of sequences of potential movements; and survey knowledge consists of geometrically-related places that emphasize the spatial relations and configurational structures. Thus, route learning is generally regarded as an associative learning process which is essentially a matter of learning actions that have to be performed under certain constraining circumstances. Route mapping usually includes direction information, but this can be relative (e.g., left, right, ahead, turn) or absolute (e.g., north, 2 o'clock, 27 degrees, and so on). Given the sequential nature of route learning, a traveler must identify the next cue in the series and activate the appropriate response at that cue site. Computational process modelers (Kuipers, 1978; Golledge, *et al*, 1983; Gärling, *et al*, 1989; Kwan, 1996) represent this process as a series of condition-action pairs or simply as a production system. If all the rules for such a system are followed, travel from a point of origin to a destination is a flawless, low-effort affair. On the other hand, configuration knowledge includes spatial relations, such as interpoint distances and directions among a set of places. This knowledge also accounts for what can be viewed from different environmental viewpoints. This is inherently spatial, and many features of this type of knowledge have evolved specifically to help wayfinding.

As pointed out by Allen (1999), while route learning is associative, configurational or layout learning is pattern learning. These cognitive and behavioral processes are represented in the various works of Kuipers (1978); Gärling and Golledge (1996); and Golledge, *et al* (1996). These models examine activity analysis in the context of cognitive maps and feasible opportunity sets (Kwan, 1994). Efforts to integrate cognitive mapping and wayfinding components into a more conventional discreet modeling framework have been undertaken by Ben-Akiva, *et al* (2000). A summary of some of the cognitive behavioral approaches in transportation modeling is contained in Allen and Golledge (2007).

Cognitive mapping researchers have established that people's knowledge of place is incomplete, distorted, and fuzzy. So, not all places within an environment are known. Golledge's anchor point theory (1978) suggests a hierarchical ordering of spatial knowledge. One consequence of this is that people are assumed to anchor their cognitive maps with specific points, lines, or areas (landmarks, road or highway sections, and neighborhoods) and that travel is often conditioned by this knowledge structure. In other words, to get from A to B, an individual might first travel to the site of or within the vicinity of a significant anchor point and then travel outward from the anchor point down a hierarchy of lesser-known paths and places until a destination is finally reached. However, it also implies that once a particular trip like this has been made up and down a place-based hierarchy, it might be possible to take a shortcut on the return route. Thus, this theory accounts for asymmetry in much travel behavior.

This type of travel also could indicate that a person's cognitive map consists of idiosyncratic as well as common knowledge of places. Idiosyncratic knowledge might consist of detailed knowledge in the vicinity of a home base, along corridors on the way to work or to shop, and in the immediate vicinity of these places or others frequently visited. Overlaying this detailed, idiosyncratic structure is a layout of commonly recognized landmarks in a particular environment. Trips to unknown destinations may take place by using part of a frequently traveled and well-known component of the city's land form and transportation structure and partly by wayfinding from a known place to an unknown destination. This implies that much travel might be inefficient.

Allen and Golledge (2007) suggest that wayfinding efforts can be placed in one of three categories: commuting (a well-established literature in transportation research), exploring (basically an information search prior to movement and during a movement to an unknown destination, partly acknowledged in the literature as travel planning (Gärling and Golledge, 2003)), and questing (travel to an unknown destination by interpreting things such as verbal directions or a map). This literature complements the general activity-based literature by emphasizing that travel is generally motivated, and identification of the motives (trip purposes) may provide insights into the nature of consequent movement. For example, in the case of commuting, travelers quickly develop travel habits, following the same procedures on all trips until disrupted by some unforeseen circumstance. Exploring seems to be more typical of social trips, particularly relating to the person-to-person interactions involved in maintaining friendships and social contacts. Questing is particularly important consequent to a migration or move within an urban system and in some shopping behavior. In the case of urban mobility, common landmark knowledge is usually maintained, but the underlying egocentric knowledge structure processed on a previous home trip may be mostly forgotten or disused and is replaced by a new set of individually important cues, route sequences, and destinations. The questions raised by Allen and Golledge extend the conventional idea of trip purpose (e.g., work, shopping, education, health, recreation, etc.) by suggesting that a trip purpose will strongly influence the way that environmental information is retained and recalled before and during movement. Thus, commuting becomes an associative learning sequentially based activity; shopping may be part exploratory and part habitual and questing may be appropriate for finding new or alternate places to visit or routes to take. But this implies that if one attempts to deal with the modeling of a population (or even a probability sample of a population), it becomes important to know what proportion of the sample (of the population) can be considered to be in one or the other of these phases. Such knowledge ideally should produce a set of equations that work together to help explain the variation that is almost always seen in travel behavior data sets.

Allen and Golledge (2007) also point out the importance of conducting further research to determine the most frequently occurring types of errors and biases that do occur in travel behavior. For example, in exploratory and questing behavior, disorientation may occur to such a degree that an individual can become lost and the consequent travel pattern may seem irregular or even random. Disorientation is often handled by reference to aids such as in-vehicle navigation systems or paper maps, or simply by examining street signs and relating them to one's long term memory base of the area in which travel is taking place. Becoming lost is often related to the idea that parts of one's cognitive map are incomplete, fuzzy, or actually missing. Thus, incomplete or only partial knowledge of a city's transportation configuration can produce erratic travel behavior. As well as disorientation, Allen and Golledge suggest misorientation can occur in many non-habitual trips. This might be so if a commonly known landmark is viewed from an unusual viewpoint or if the commonly known landmark is mistaken for another similar one (e.g., two architecturally similar skyscrapers or other buildings). Misorientation is sometimes referred to as directional bias, induced by the development of a corridor-type knowledge structure anchored by well-established travel habits. Distance bias results in under or over estimation of travel time and travel distance. Such a bias occurs most commonly when traveling to lesser known or unknown areas of an environment. Needless to say, the influence of these types of errors and biases has not yet been incorporated into predictive models of travel behavior, because so little is known about them. This is obviously an area of potentially fruitful further research. It can generally be accepted that the provision of aids such as in-vehicle information systems (IVNS) have been developed in an attempt to deal with errors and biases made while traveling. Research with the relevant companies, such as On-Star, might provide further evidence of which type of travel purpose is most likely to produce types of error and biases—in particular, the case of becoming lost.

Urban travel consists of a combination of habitual behavior, and several types of wayfinding behavior (exploratory and questing behaviors). Research in behavioral geography and cognitive psychology has only recognized these wayfinding characteristics over the last decade or so. There is still insufficient information about the details of urban wayfinding procedures to allow ready incorporation of features such as cognitive map knowledge and exploratory or search strategies into the more general population-based wayfinding models. Because of this, there has been little movement to incorporate wayfinding into evacuation or other homeland security-related modeling. To date, behavioral research in the US has been limited to population evacuation during hurricanes, earthquakes, and large wildfires mainly because other types of events, such as terrorist attacks, have been limited. While recent efforts have attempted to incorporate more behaviorally-related elements into the models, most of the transportation-related modeling still does not include how people select their evacuation routes. For example, while many models select the fastest set of local streets to gain access to an evacuation route, it might be more likely that an individual would choose more round-a-bout access route to avoid traffic. For example, Dow and Cutter (2002) interviewed people who evacuated South Carolina in advance of Hurricane Floyd making landfall in 1999. They found that while the majority of respondents carried road maps, only 51% of that group used them to determine their route. One long-term goal of activity-based modeling for homeland security applications should be to incorporate more of the previously identified behavioral modeling paradigms and components into travel behavior models. The next section contains an overview of most the activity-based approaches that have been used in travel behavior modeling to date.

ACTIVITY-BASED MODELS

Activity-based modeling has been a focus of transportation research for almost forty years. During this time, a variety of approaches have been studied and incorporated in actual applications. With the increasing availability and capacity of computers and electronic data, the models have become more sophisticated by attempting to incorporate more behavioral components and finer spatial and temporal resolutions in developing activity schedules and movements across a network. These types of models are only now being considered for use in homeland security-related applications. Below is a detailed look at available methodologies.

Activity-Based Approaches

Activity-based models previous developed or currently in use today utilize one or more decision-making paradigms, which result in a variety of different types of methodologies to model travel behavior. In general, these methodologies include microeconomic optimizers, which assume that people maximize something such as travel time or costs, computational process models, which attempt to mimic observed human behavioral processes, naïve data-driven models, which extract models from observed outcome data, early versions of satisficing models, which attempt to limit the number of choices available to simulated individuals, and cellular automata, which apply physics principles to mimic human behavior.

The first models that began to incorporate behavioral processes into the methodologies were published in the late 1970's and early 1980's. As seen in Table 1, many of these models either utilized time-prism constraints, such as BSP (Huigen, 1986), and the Computational Algorithms for Rescheduling Lists of Activities (CARLA) (Jones, *et al*, 1983), or data-driven statistical distribution utility-maximizing models, including the Adler and Ben-Akiva model (1979) and the Kawakami and Isobe model (1989). According to Lenntorp (2006, pers. comm., March 27), PESASP (Lenntorp, 1976), one of the first models to operationally show the use of a time-prism in one area, was designed to show it is essential to view a whole sequence of activities and not just individual journeys. The Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions (STARCHILD- Recker and McNally, 1986a,b) applied both these mechanisms in a utility-based model with constraints. SCHEDULER (Gärling, *et al*, 1989) was the first model framework to incorporate a computational process model (CPM), adding a psychometric cognitive basis first proposed by Hayes-Roth and Hayes-Roth (1979). In SCHEDULER, activities, selected from the long term calendar that represents a person's long term memory, comprise a schedule that is "mentally executed". Each of these models generate activity patterns, with either no actual time-of-day estimate or, as is the case with CARLA, each activity to be considered by the model is required to have a duration and a time window in which the activity needs to occur supplied as an input. Spatial information such as specific locations where activities are pursued is not considered as part of these models.

The first model to include a microsimulation in its paradigm is ORIENT (Sparmann, 1980). This methodology was proven in a real application for the Netherlands in 1992 when Goulias and Kitamura built the longitudinal econometric model called the Microanalytic Integrated Demographic Accounting System (MIDAS- Goulias and Kitamura, 1992, 1997), and converted for the US by Chung and Goulias, 1997), which simulates the evolution of households along with car ownership and travel behavior. The Activity Mobility Simulator (AMOS) (Kitamura, *et al,* 1996), which uses a neural network to identify choices and a satisfying rule to simulate schedule changes, is also a microsimulation that uses a different modeling paradigm. While MIDAS is a strictly longitudinal process econometric model progressing one year at a time, AMOS is constraint-based model designed for finer temporal resolution.

In the mid-1990's, a large number of activity pattern models were released utilizing a wide variety of paradigms. Ettema, *et al* released the Simulation Model of Activity Scheduling Heuristics (SMASH) (1996) and COMRADE (1995), both in 1995. SMASH is a CPM and econometric utility-based hybrid model that focuses on the pre-trip planning process. It focused on the sequence of activities; as such it did not model duration. This was one of the focus areas of COMRADE. A competing risk hazard model that is applied directly to activity scheduling, it is able to incorporate the continuous nature of decision making. (H. Timmermans, 2006, pers. comm., March 14) The Model of Action Space in Time Intervals and Clusters (MASTIC- Dijst and Vidakovic, 1997), which uses data-driven statistical distributions, Household Activity Pattern Problem (HAPP-Recker, 1995), an optimization model, the Prism-Constrained Activity-Travel Simulator (PCATS-Kitamura, 1997), a utility-based model, and the GIS-Interfaced Computational-process modeling for Activity Scheduling (GISICAS-Kwan, 1997), a simplified CPM, all utilize time-space constraints from time geography. Ma (1997) also developed a model system that combined long term activity patterns (Long-term activity and travel planning — LATP) with a within-a-day activity scheduling and simulation (Daily Activity and Travel Scheduling — DATS) incorporating day-to-day variation and history dependence. Her model system is based on panel surveys (the repeated observation of the same persons and households over time). In the LATP/DATS system longitudinal statistical models are extracted from longitudinal records and they capture important aspects of behavioral dynamics such as habit persistence and day-to-day switching behaviors.

However, the theory behind each of these models varies greatly. MASTIC identifies clusters in the action space to perform and schedule activities. HAPP, a variant of the pick up and delivery time window problem, optimally creates activity schedules. PCATS applies time-space prisms as constraints to generate activities and trips for individuals. GISICAS, a simplified, operational version of SCHEDULER, employs a Geographic Information System (GIS) to incorporate spatial information into the model to create individual schedules, starting with high priority activities. Other models also attempt to recreate personal schedules such as Vause's model

(1997), a CPM that creates a restricted choice set for creating activity patterns, a model by Ettema, *et al* (1997), and VISEM (Fellendorf, *et al*, 1997), a data-driven statistical distributions model that is a part of PTV Vision, an urban and regional transportation planning system, that creates daily activity patterns for behaviorally homogeneous groups within the population. Similarly, two new modeling frameworks were also proposed. Stopher, *et al* proposed the Simulation Model for Activity Resources and Travel (SMART-1996) in 1996. SMART, using a time geography framework, envisions creating activity patterns for households based on three types of activities — mandatory, flexible, and optional — inside a GIS environment. Another framework, the Daily Activity Schedule model was published by Ben-Akiva, *et al* in 1996. This model, used to create the Portland Daily Activity Schedule Model (Bowman *et al*, 1998), advocated modeling lifestyle and mobility decisions on a scale of years. These influence daily activity schedules, which are comprised of primary and secondary tours constrained in time and space.

Microsimulations continued to be developed during this same time period. In 1995, the Transportation Analysis Simulation System (TRANSIMS-LANL, an extension of TRANSIMS 3.1.1 available via a NASA open source license from TMIP), a data-driven cellular automata microsimulation, was developed at Los Alamos National Laboratory (2003). It was one of the first simulation packages to contain models that create a synthetic population, generate activity plans for individuals, formulate routes on a network based on these, and execute the activity plans. In 1997, another daily activity-travel pattern model was estimated using the 1990 Southern California Association of Governments (SCAG) travel dairy. This data-driven statistical distributions model, created by Kitamura, *et al* (1997), is a sequential approach for creating activity-travel patterns for a synthetic population. A year later in 1998, MatSIM, an econometric utility-based model with microsimulation, was released (Balmer et al, 2008). The model employs a basic evolutionary (relaxation) strategy to develop travel patterns. Initial activity schedules are used to generate traffic inside a microsimulation. The actual travel times for the schedules are calculated. These are used update the previous schedules. The process is repeated until equilibrium is obtained. Also in 1998, ALBATROSS was released by Arentze and Timmermans (2000). ALBATROSS is a multi-agent CPM that predicts the time, location, duration, and with whom activities occur as well as the type of mode utilized, subject to spatio-temporal, institutional, and household constraints. One of the most comprehensive operational activity-based models, it incorporates a large number of choice facets, uses a detailed classification of activities, and includes a wide set of constraints. However, it does not simulate route choice. Development of the third version of ALBATROSS is currently underway. (H. Timmermans, 2006, pers. comm., March 14) To determine whether the heavily theory-driven activity schedule representation of ALBATROSS was important, the Regional planning Model Based on the microsimulation of daily Activity Patterns (RAMBLAS), published in 1999 by Veldhuisen, *et al* (2000), was developed. RAMBLAS is a data-driven statistical distributions microsimulation that applies time-space constraints. Survey participants are placed into representative groups of the population based on socio-economic demographic information, linked to housing characteristics. Then, full day activity patterns are assigned to simulated individuals drawn at random from a national survey, matched in terms of socio-demographics, classification of urban environments and main transport mode. (H. Timmermans, 2006, pers. comm., March 14). Similarly, SIMAP (Kulkarni and McNally, 2001) divides a survey population into groups, based on representative activity patterns (RAPs). These classifications are used to create full day activity patterns. Like SIMAP, DEMOS (Sundararajan and Goulias, 2003), also released in 2000, is a microsimulation that utilizes data-driven statistical distributions. DEMOS is designed to simulate the evolution of people and their households using the Puget Sound Transportation Panel. It also simulates activity participation, travel, and telecommunication market penetration using a few representative patterns.

Non-microsimulations continued to be formulated from the late 1990's. As previously mentioned, the Portland Daily Activity Schedule Model, based on the Daily Activity Schedule Model framework, uses integrated disaggregate discrete choice models to determine an individual's demand for activity and travel as an activity pattern and set of tours. PETRA, another data-driven statistical distributions model, was formulated by Fosgerau in 1998 (2001). This model utilizes a less complicated paradigm that only models home-based tours for the purpose of work, errands, and leisure. The time dimension and sequencing of activities on a tour are both ignored. This allows the model to work with a low number of daily travel patterns, which has statistical advantages. (M. Fosgerau, 2006, pers. comm., March 13) A model with high spatial resolution, the Alam Penn State Emergency Management model (Alam-PSEM, Alam and Goulias, 1999) is a building-by-building simulation of activity participation and presence at specific locations of the University Park campus for each hour of a typical day. In 1999, Bhat and Singh (2000; Baht, 2001) estimated the Comprehensive Activity-Travel Generation System for Workers (CATGW), a series of econometric models that replicate a commuter's evening mode choices, number of evening commute stops, and the number of stops after arriving home from work. Another econometric model, the Conjoint-Based Model to Predict

Table 1: Activity-based Model Paradigms

Model	Cellular Automata	Constraints	CPM	Data-Statistical Distributions	Econometric Utility-Based	Frame-work	Psychometric Hazards Risk	Micro-simulation	Operations Research	
ADAPTS			X			X				
Adler and Ben-Akiva				X						
Alam PSEM				X						
ALBATROSS			X					X		
AMOS		X						X		
AURORA		X			X					
BSP		X								
CARLA		X								
CATGW					X					
CEMDAP					X			X		
CentreSIM - medoid				X						
CentreSIM – regional				X						
COBRA					X					
COMRADE							X			
Daily Activity Schedule						X				
DATS/LATP		X		X				X		
DEMOS				X				X		
Ettema (HCG)						X				
FAMOS		X	X					X		
FEATHERS		X			X			X		
GISICAS		X	X							X
HAPP		X							X	
Hayes-Roth & Hayes-Roth			X							X
ILUTE			X		X			X		
Jakarta					X			X		
Kawakami & Isobe		X		X						
MASTIC		X		X						
MatSIM					X			X		
MERLIN			X					X		
MIDAS					X			X		
MORPC				X				X		
NY “Best Practice”				X				X		
ORIENT				X				X		
PATRICIA				X	X					

PCATS		X			X					
PESASP		X								
PETRA				X						
Portland Daily Activity Schedule				X						
PUMA		X			X					
RAMBLAS		X		X				X		
San Francisco				X				X		
SCHEDULER		X	X			X				X
SIMAP				X				X		
SMART						X				
SMASH			X		X					
STARCHILD		X			X					
Synthetic Daily Activity-Travel Patterns				X		X		X		
TASHA			X	X	X			X		
Tel Aviv					X					
TRANSIMS-LANL	X							X		
Vause			X							
VISEM				X						
Wen and Koppelman				X						

Regional Activity Patterns (COBRA), developed by Wang and Timmermans in 2000, generates general patterns of stops for specific activities using a conjoint-based model with stated preference data in place of the typically used travel or activity diary. The Wen and Koppelman model (2000) utilizes three layers of decisions that are influenced by exogenous variables to generate activity patterns. The first layer contains household subsistence and mobility requirements. The second layer contains the maintenance activity generation and the allocation of vehicles, and stops. The third layer creates activity patterns with the generation of tours, assignment of stops to tours, the type of mode, and the location the activity occurs. Another data-driven statistical distribution model, the CentreSIM regional model (Kuhnau and Goulias, 2002, 2003; Goulias, et al, 2004) uses time-of-day activity and travel data for different market segments to predict hour-by-hour presence at locations and travel between zones. In 2002, PATRICIA (Predicting Activity-Travel Interdependencies with a Suite of Choice-Based, Interlinked Analyses), a data-driven statistical distributions and econometric utility-based hybrid, was developed by Borgers, *et al* (2002) to help assess the performance of ALBATROSS. PATRICIA is a suite of linked models that incorporates and expanded set of activity choices, based on 63 distinct patterns, and activity destinations and describes activity transport modes and sequences. A complementary model to ALBATROSS, AURORA (Timmermans, et al, 2001; Joh, et al, 2004) is a utility-based system that models the dynamics of activity scheduling and rescheduling decisions as a function of multiple choice facets. First released in 2003, AURORA focused on short-term adaptation and rescheduling, using just a few critical parameters as opposed to the many decision tables and rules in ALBATROSS. The model has since been expanded to include decision making under uncertainty and reaction to travel information. It has also been linked to a multi-agent simulation. (H. Timmermans, 2006, pers. comm., March 14) In 2004, as a part of the Longitudinal Integrated Forecasting Environment (LIFE) framework (Goulias, 2001), Pribyl and Goulias (2005) developed CentreSIM (medoid simulation) to derive a few representative patterns and simulate daily schedules accounting for within-household interactions for entire daily patterns. Most recently, D. Ettema *et al* (2006) have been working on developing PUMA (Predicting Urbanization with Multi-Agents), a full-fledged multi-agent system of urban processes that represents land use changes in a behaviorally realistic way. These processes include the evolution of population, businesses, and land use as well as daily activity and travel patterns of people. To simulate activity-travel patterns, an updated version of AURORA will be incorporated. Shiftan and Ben-Akiva (2006) have also been implementing an econometric utility-based model for Tel Aviv. The model first determines destination, mode, and time period of the primary destination. Then, additional stops and secondary tours are added if necessary, based on probabilities. A new computational, rule-based framework called Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) is being developed by Auld and Mohammadian (2009). It is designed to generate activities based on survey data. The activities are then scheduled based on a series of rules derived from scheduling process data. The model is unique in that it treats activity planning and scheduling as dynamic events within the simulation. The model will remove the sequential fixed order assumption for activity attribute planning, based on the collection of attribute planning horizon data. (Mohammadian, 2008, pers. comm., August 26)

Microsimulations continued to evolve in another direction. The Integrated Land Use, Transportation and Environment (ILUTE) model (Salvini and Miller, 2003) model is designed to simulate the evolution of people and their activity patterns, transportation networks, houses, commercial buildings, the economy, and the job market over time. Another model developed by Miller and Roorda (2003), the Toronto Area Scheduling model for Household Agents (TASHA) uses projects to organize activity episodes into schedules of persons. Schedules for members in a household are simultaneously generated to allow for joint activities. Both ILUTE and TASHA utilize CPMs and econometric utility-based paradigms. A microsimulation that uses econometric models to simulate daily activity travel patterns for an individual, the Comprehensive Econometric Microsimulator for Daily Activity-travel Patterns (CEMDAP) model (Bhat, et al, 2003) is based on land use, socio-demographic, activity system, and level-of-service (LOS) attributes. Initially released in 2003, it is continually being expanded. The current version of CEMDAP includes the activity-pattern generation and scheduling of children. (C. Bhat, 2006, pers. comm., March 13 and April 14) MERLIN, a CPM and econometric utility-based hybrid from Van Middelkoop, *et al* (2004) that basically uses the same approach as ALBATROSS, estimates leisure and vacation activity travel patterns on an annual basis. (H. Timmermans, 2006, pers. comm., March 14) Another model that utilizes constraints is the Florida Activity Mobility Simulator (FAMOS) (Pendyala et al, 2005). FAMOS encompasses two modules, the Household Attributes Generation System (HAGS) and PCATS. Together, they comprise a system for modeling the activity patterns of individuals in Florida. The output is a series of activity-travel records. FAMOS is currently being further enhanced to include intra-household interactions and capture task allocation behavior among household members. More recently, Arentze, *et al* (2006) have been working to extend AURORA as part of the model FEATHERS (Forecasting Evolutionary Activity-Travel of Household and their Environmental Repercussions) to simulate activity-level scheduling decisions, within-a-day rescheduling, and learning processes in high resolution time and space. Developed as a complimentary to ALBATROSS, FEATHERS is econometric utility-based microsimulation that utilizes constraints that focuses on the short-term dynamics of activity-travel patterns. Microsimulations have continued to gain in popularity in the activity-based modeling universe as they move from research applications to practice. Besides the Portland Daily Activity Schedule Model mentioned previously, New York's "Best Practice" Model (2002) and the Mid-Ohio Regional Planning Commission (MORPC) Model (2003), both developed by Vovsha, et al, and the San Francisco model (Jonnalagadda, et al, 2001) are currently being utilized by their respective MPO. The San Francisco model is currently being updated to implement enhanced destination choice models and being recalibrated using more recent household and census data. (J. Freedman, 2006, pers. comm., March 28) Four other models for Atlanta, Sacramento, the Bay Area, and Denver are currently in various stages of implementation. (Bradley and Bowman, 2006) One of the first activity-based models utilized in a developing country was completed by Yagi and Mohammadian (2006, 2008) for Jakarta. It is an econometric utility-based model with microsimulation, designed to evaluate traffic management policies, such as restricting central arterial roads to only allow high occupancy vehicles during peak periods and implementing a new bus rapid transit system.

The majority of the activity-based transportation models included in this review do not deliberately incorporate any behavioral principals in their design. Only the frameworks for SCHEDULER, a highly influential design, and SMART, whose theory was never fully developed, along with ADAMPTS (a framework in the process of being implemented), ALBATROSS, and FEATHERS have attempted to include explicit consideration and models of knowledge and memory as well as behavioral process for planning activities. However, the need to include more behavioral elements is starting to become more prominent as the activity-based models become more sophisticated. The need to include intra-household interactions has become an important research topic. ALBATROSS, CEMDAP, FAMOS, FEATHERS, ILUTE/TASHA, and, to an extent, TRANSIMS-LANL have either already included or are in the process of adding the capability to assign family members activity patterns that allow interaction with each other (table 2). This importance is reflected in the activity-based models used in practice by MPOs as well. MORPC has the capability to model intra-household interactions and the models in development for Atlanta and the Bay Area will have these types of interactions as well. Without more research to extend current modeling to include these elements, activity-based homeland security applications will be limited in their ability to incorporate activity scheduling in emergency situations. Dow and Cutter (2002) determined that 25% of all households evacuating South Carolina from Hurricane Floyd in 1999 took more than one car. Activity-based approaches that do not allow families to schedule intra-household activities will not be able to capture this behavior. At a more sophisticated level, as previously pointed out, none of the models are able to replicate wayfinding behavior in developing non-emergency schedules. Therefore, there is no way to generate travel patterns that reflect how people select travel routes in the uncertainty of an emergency situation.

Temporal and Spatial Resolution Model Requirements

In the past, MPOs relied on "typical" travel represented by large blocks of time (i.e., 3-4 hours in length) and space (TAZs can vary in size from blocks to census tracts) to drive define modeling parameters. However, as noted previously, this is not suitable for either policy issues or evaluating homeland security issues. Depending on the type of event (natural or manmade), critical spatial and temporal constraints can develop that would best be represented by high resolution modeling.

The majority of the activity-based models have undefined or large time resolutions. As shown in table 3, with the exception of STARCHILD (1986) with a temporal resolution of 15 minutes, it wasn't until 1995 that several models were released with relatively small time intervals: COMRADE (continuous), HAPP (15 minutes), MASTIC (minute), and TRANSIMS-LANL (second). Currently, many of the newer research-based models have incorporated smaller time resolutions. SIMAP and TASHA have 10-minute and 5-minute intervals, respectively. CentreSIM (medoid), MASTIC, GISICAS, and RAMBLAS have one minute increments. ILUTE and PUMA, in theory, varies depending on what type of simulation is being run. Besides COMRADE and TRANSIMS-LANL, ADAPTS (in theory), ALBATROSS, AURORA, CATGW, CEMDAP, FAMOS, FEATHERS and MatSIM are the only other models that can be run on a second-by-second or continuous basis. Of the models currently used in practice by an MPO, only one model, MORPC, operates with the relatively small time resolution of one hour. However, the four newer MPO models that are in the process of being designed and implemented will have temporal resolutions of 30 minutes to one hour (Bradley and Bowman, 2006), which is a vast improvement over the standard four or five blocks of time these first activity-based models applied.

Table 2: Behavioral Units

Decision Makers	Groups Modeled					
	Unknown/ Unspecificed	**Workers**	**College Students**	**Adults**	**Partial Households**	**Entire Households**
Unknown/ Unspecified	BSP				PESASP (16 yrs +)	
Individuals	Daily Activity Schedule, Hayes-Roth & Hayes-Roth, PCATS, SMART, Vause	Alam-PSEM, AMOS, CATGW, COBRA	Alam-PSEM, COMRADE	AURORA, DATS/ LATP, FEATHERS, MASTIC, PATRICIA, SIMAP, Synthetic Daily Activity-Travel Patterns	Portland Daily Activity Schedule (16 yrs +), Tel Aviv (7 yrs +), Wen and Koppelman (married couples)	ADAPTS, CARLA, CentreSIM – regional, Ettema et al's (HCG), GISICAS, HAPP, Jakarta, MatSIM, MORPC, NY "Best Practice", PETRA, RAMBLAS, San Francisco, SCHEDULER, SMASH, STARCHILD, TRANSIMS-LANL
Households				ALBATROSS		Adler and Ben-Akiva, CEMDAP, CentreSIM– Medoid, DEMOS, FAMOS, ILUTE, MERLIN, MIDAS, PUMA, TASHA
Specified Groups						ILUTE
Workers		Kawakami and Isobe				
Homogenous Population Groups	ORIENT				VISEM (10 yrs +)	

However, as can be demonstrated above, there is still much room for improvement in temporal elements of these consultant-designed models.

When evaluating spatial resolution (table 3), even fewer models are able to process data below a zonal level. ALBATROSS and MORPC both can operate at the sub-zone level. ADAPTS is designed to use zonal down to parcel-level data, depending on the destination location model finally implemented. Alam-PSEM, AURORA, CEMDAP, FEATHERS, GISICAS, ILUTE, MatSIM, PUMA, SIMAP, SMASH, and TRANSIMS-LANL are the only models able to utilize data at essentially the building or point level. None of the models currently used by MPOs have spatial resolutions below the zonal level. Overall, only eight models have a reasonable spatial, temporal, and behavioral resolution. They are ADAPTS (when fully implemented), ALBATROSS, CEMDAP, FEATHERS, ILUTE, MatSIM, PUMA, and TRANSIMS-LANL. However, these models still do not incorporate all the desired elements to truly make a fully functional application for modeling homeland security events with a strong behavioral component in developing schedules for entire households in an emergency situation that incorporates movements a high space and time resolution.

DATA AND INFORMATION GAPS

Although substantial progress is observed in the activity-based travel demand forecasting methods and in the integrated land use transportation modeling arenas, we still have many critical areas for further improvement. The list below is developed with focus on homeland security applications.

Research

According to the Transportation Research Board's Surface Transportation Security website (TRB, 2008), the majority of the general transportation security activities have been exclusively confined to operations. Very little, if anything, has been devoted to applying activity-based models in homeland security applications.

Identify and Inventory Residence Locations

Complete coverage of all the locations in the US can be achieved when we use multiple source of information and databases that are available in the public domain (e.g., excluding tax records and original Census data). For complete coverage, the ideal and most detailed geographic unit is a parcel of land. Public records of parcels exist in tax assess-

Table 3: Activity-based model spatial and temporal resolutions

Spatial Resolution	Temporal Resolution							
	Unknown/ Unspecificed	None	Year	Blocks of Time	Hour	5 to 30 Minutes	Minute	Second or Continuous
Unknown/ Unspecified	BSP, Ettema (HCG), Hayes-Roth and Hayes-Roth, Kawakami and Isobe, ORIENT, Wen and Koppelman					Starchild		
None	Vause, CATGW	Adler and Ben-Akiva, Daily Activity Schedule, PESASP, SCHEDULER, SMART	MIDAS, DEMOS	CARLA, COBRA, Synthetic Daily Activity-Travel Patterns		HAPP	CentreSIM - medoid	COMRADE, DATS/LATP
Region			MERLIN					
Zones	AMOS	PATRICIA		Jakarta, NY "Best Practice", PCATS, PETRA, Portland Daily Activity Schedule, San Francisco	VISEM, CentreSIM - regional	TASHA, Tel Aviv	MASTIC, RAMBLAS	FAMOS
Sub-zones					MORPC			ALBATROSS, AURORA. FEATHERS
Points		SMASH			Alam PSEM	SIMAP	GISICAS	ADAPTS, CEMDAP, ILUTE, MatSIM, PUMA, TRANSIMS-LANL

ments and they are becoming more available on the internet. These records contain details about the parcel and the buildings within it including sizes and building characteristics. Contrary to what one would expect, this information is not commonly used either as the primary source of data or as a validation and verification tool. For example, the value of the properties in each parcel and its general neighborhood characteristics can be used to more precisely "allocate" households to specific geographic locations as residents.

Include Time Constraints

When formulating activity schedules, many of the models do not utilize the constraints of operating cycles for businesses. Since the time of day being modeled, or even the time of year, will result in great differences in activity patterns, this type of information must be evaluated. For example, doctor's offices are only open for patients during the day. In smaller communities, they may close early a few afternoons a week. The constraints of operating cycles for businesses must therefore be included.

Modeling Short-Term Changes

While long-term modeling has received a great deal of attention, short term modeling of changes in business locations and land use has been neglected. Many of the existing datasets are only updated annually, so determining the types of changes that occur on a monthly basis may be important in homeland security modeling. For example, a doctor office moves to a new location and another business moves in. Unless the same mix of businesses is maintained in the area, research has shown that traffic patterns could change. The same issue exists for residential changes — if a house is sold, is the buyer following the same activity pattern as the original owner? Research concentrating on updating or forecasting changes in small increments is needed.

Filling Gaps In Surveys

The majority of the activity-based models are based on survey micro-data. Therefore, missing sub-populations in surveys such as children, the homeless, and marginalized individuals, can result in large numbers of missing activity patterns. While there are methodologies to account for missing populations, how accurately are these applied? Are researchers actually spending time to properly identify these missing people? In homeland security-related modeling, missing sub-populations of people could result in misidentifying persons that could be affected in a national security event.

Account for Fleets, Services, and Goods

At any point in a day a large number of vehicles arrive to and depart from businesses and residence to deliver goods but to also deliver services (e.g., gardening, maintenance, construction). Stefan, *et al* (2005) estimate these vehicles to be approximately 15% of the observed traffic. All the models reviewed here neglect this aspect of activity participation and travel as well as human interaction.

Modeling Inter- and Intra-Household Interactions

Srinivasan and Bhat (2006) have demonstrated empirically through the analysis of the American Time Use Survey that a significant number of trips are made with both non-household (friend, co-workers) and household members. Only a small number of activity-based models actually have attempted to include interactions between family members. None of them have attempted to account for activity patterns based on interactions between households or individuals in organizations yet, although the frameworks for FEATHERS and ILUTE do show the intent to include these.

Weekly and Seasonal Variations

The models developed for public policy suffer from the original purpose of modeling emission and air pollution from internal combustion engines at the regional level for conformity assessments. For this reason seasonality of behavior is not accounted for (although a typical summer day may not be very typical for activity and travel behavior). Recent changes in shopping behavior are also motivating analysis of weekday versus weekend travel that may help homeland security applications that require estimates valid all year.

Activity Scheduling in Panic and Emergency Conditions

As far as we are aware, no one in the activity-based transportation modeling community has ever attempted to create activity patterns based on high stress or panic conditions. Since we need to model an incident such as the release of a dirty bomb, people will no longer operate under "normal conditions". We need to understand behaviors under these circumstances. For example, more cross-over research between transportation researchers and cognitive specialists must occur in order to begin to understand this type of behavior and determine how activity patterns in this type of situation are formulated and executed.

Behavioral Errors and Biases

As discussed earlier, the relationship between travel and information can be examined in the three categories of commuting, exploring, and questing. Travel under time pressure and fear (called panic herein) is absent from all this. Within this context the two errors and biases described in this paper, disorientation and misorientation are just two of the many possible examples of behavioral errors and biases that we need to explore and understand in more detail.

SUMMARY AND CONCLUSIONS

Substantial progress is observed in the past 25 years in travel demand modeling and simulation and a variety of new ideas emerge as potentially useful for homeland security applications. For example, many models use hybrid paradigms that are combinations of statistical/econometric models and CPM to represent behavior. Others use statistical models embedded into microsimulation frameworks to evolve either individuals and/or households over time. Overall, we are ready for the next major step in modeling and simulation to develop multipurpose, high resolution, and behaviorally informed spatio-temporal models of cities.

As expected, however, modeling and simulation appears to be concentrating at two poles. They are either designed for the long term with yearly cycles or the very short term such as within-a-day activity patterns. In spite of a major push toward better representation of human life many critical gaps are found in representing the entirety of our social spectrum, model capability to represent activity and travel pattern on a second-by-second basis, and modeling of people's presence at each parcel of a city. These are all potentially solvable issues using additional resources to acquire data. In addition, other temporal dimensions such as weekly, monthly, and seasonal regularities could conceivably be resolved with proper data collection and analysis.

Moreover, a few additional areas on inter- and intra-household interactions and activity scheduling in panic and emergency conditions are also identified as the neglected aspects in the behavioral analysis arena and they are not easily solvable by simple investments. Finally, another key aspect that is receiving some attention in pioneering research efforts is the issues of spatial cognition and behavior in familiar and unfamiliar contexts.

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