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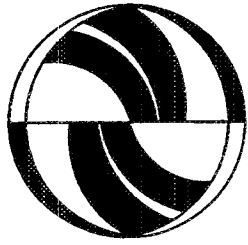https://escholarship.org/uc/item/91f574zq

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Computational Process Modeling of Disaggregate Travel Behavior

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Abstract. In this paper we review attempts to develop CPM of individual travel behavior. CPM represent a linked set of computer programs together with appropriate databases which are designed to capture the essence of human decision making in different spatial situations. Used primarily for wayfinding and to simulate and predict travel behavior, CPMs bypass the difficult problems of IIA typically attributed to discrete choice models. They also allow greater emphasis on the cognitive components of decision making including cognitive maps, preferences, and departure from utility maximizing and linearity in the considerations of alternative paths and alternative destinations. The CPM illustrated herein focuses on multiperson households and models travel behavior before and after telecommuting takes place in the household. Sets of feasible alternative destinations for travel purposes are derived using GIS procedures such as buffering and path selection. Shortcomings and possible future developments of such models are then discussed.

1 Introduction

It is common for researchers adopting an activity based approach to travel behavior to differentiate between behaviors that are routinized and behaviors that result from deliberate choice. For example, a significantly large part of work-trip behavior is routinized; individuals tend to use the same mode for each trip, to leave their home base at approximately the same time, to aim at arriving at approximately the same time at their work place, and to follow the same route and the same path segments that make up that route. Some other trip purposes are similarly routinized such as trips for religious purposes, and trips for medical or health related reasons - routinized in the sense of using the same mode and

following the same path, even though the times at which travel may be undertaken might vary because of temporal differences in the scheduling of appointments by health professionals. Other trips such as grocery or food shopping may be routinized to a lesser extent. Instead of choosing a single destination and following a repetitive path to that destination, several alternative destinations may be kept as part of a feasible alternative set. Trip making on any given day then becomes more of a deliberate choice both in terms of selecting a specific destination and in terms of selecting the travel path. Variation can also occur in terms of travel mode. Many other trip purposes fall within the deliberated choice purview. In particular trips for social or recreational purposes, trips to meet with friends, trips undertaken for the purpose of dining away from home, business trips, and so on, all may be scheduled with different episodic intervals or frequencies, different lengths or durations, different destinations, different temporal units, different priorities, different sequences, as well as being undertaken either as single purpose or multiple purpose trips with single stop or multiple stop destinations.

While the modeling of the routinized choices and the prediction of consequent travel behavior has been achieved with a considerable degree of success using discrete choice models, dynamic Markov models, and even via variations of the fundamental spatial interaction or gravity type models, less success has traditionally accrued when trying to model behaviors resulting from deliberated choice. As part of the effort to model, explain, and predict trip making, geographers and transportation scientists generally have developed or adopted a number of strategies that focus either on network characteristics (shortest path models), aggregate behaviors (spatial interaction model and entropy models), individual preferences (compositional and decompositional preference modes), and choice models (discrete choice models, models of variety seeking behavior, compositional and decompositional choice models) (Timmermans and Golledge, 1990). Discrete choice models have also been used in transportation science for the modeling of choices of modes, departure times, or other characteristics relating to how single trip choices and choice alternative characteristics match up, or to the extent to which individual trip making behavior matches the behavior of a group to which they are assumed to belong.

The seminal work of Jones, Koppelman and Orfeuil (1990) firmly established a mutual dependency between travel choices and household or individual's agenda of activities. Previously, Root and Recker (1983) had suggested that choices of destinations, departure times, and frequency and duration of activity participation should all be treated in a single conceptual framework that entails behavioral assumptions accounting for the process of making these interrelated choices. In other words, they developed the idea of focusing on the activity scheduling process and defining the type of model whose input consisted of components of this scheduling process. While this approach was conceptually and theoretically appealing, it proved difficult to implement within the context of the existing

transportation and behavior models, particularly the dominant discrete choice modeling framework that existed at that time.

As an alternative, a new form of modeling of travel behavior began to develop based on the idea of a set of interacting computer programs which would relate elements of real and perceived environments, factors influencing choice of destination, household preferences for scheduling activity sequences, and a variety of authority, coupling, and capability constraints that had been offered as part of the emerging field of time geography (Hägerstrand, 1970; Carlstein, Parkes and Thrift, 1978). Simultaneously, awareness of the limitations of simple discrete choice models encouraged the development of tools suitable to model interdependent or joint choices, which include the nested logit (Ben-Akiva and Lerman, 1985; McFadden, 1979) or structural equations models (Golob and Meurs, 1988) evolved. Axhausen and Gärling (1992) have summarized other attempts at estimating discrete choice models in which activities are important components and include summaries of the works of Kitamura (1988), Thill and Thomas (1987), and the trip-chaining models of Damm and Lerman (1981), Kitamura, Nishii and Goulias (1990), and activity choice and activity duration (Kitamura, 1984). Following the lead of Root and Recker (1983) activity based choice models emerged (Recker, McNally and Root, 1986a and 1986b), along with some econometric research on time allocation (Winston, 1987). Much of this work, however, invariably rested on utility maximizing assumptions. Questioning of this assumption had been extensive in psychology (Simon, 1955 and 1990; Tversky and Kahneman, 1991 and 1993) as well as in transportation research (Supernak, 1992). In general, these models were limited in that they specified the factors affecting final choice but neglected the processes resulting in these choices. Obviously if the primary aim is to forecast travel choices, this criticism is not an important one; but if the goal is to understand the entire process and to develop appropriate relevant theory, then the shortcoming does become significant.

In a style similar to the STARCHILD model developed by Recker, et al. (1986a and 1986b) another alternative model format called Computational Process Modeling (CPM) emerged. In an activity scheduling context, these Computational Process Models (CPM) focused on interdependent choices where choice involved acquisition, storage and retrieval of information, including retrieval from long-term memory, tradeoffs between accuracy of recalled information concerning locations, hours of business, and remembered paths, in terms of effort (time or distance) expended in order to make the tradeoff and achieve a goal. It also included the possibility for a conflict resolution where uncertainty may exist in terms of competition for a travel mode (e.g., who gets the household car), which activities are considered primary and which secondary and therefore take precedence in scheduling, and which destination choices provide the greatest flexibility and judge success in terms of completing a planned activity schedule. These models are built on some of the seminal ideas of Hayes-Roth and Hayes-Roth (1979) who produced a production system model

which was accepted as a feasible alternative to existing discrete choice models for travel behavior analysis.

Production systems were initially developed by Newell and Simon (1972) as elaborations of how people think when they solve problems. They are frequently used in theories involving the higher cognitive processes (Anderson, 1990; Newell, 1992). Essentially a production system is a set of rules in the form of condition-action pairs that specify how a task can be solved. If the task requires an individual to choose one alternative in a choice set, the rules may specify what information is searched under different conditions, how the information is evaluated, how the evaluation or judgments are integrated. The system is usually realized in terms of a cognitive architecture comprising a perceptual parser, a limited capacity working memory, a permanent long-term memory, and a system for effecting a behavior. An operational CPM is a production system implemented as a computer program. The resulting CPM offers a test-bed for assessing the consequences of different policy measures, or as a mechanism for facilitating the development of different testable hypotheses. One may also incorporate different testable assumptions into the model to examine their effects on potential choice and consequent behavior.

Essentially a CPM was assumed to be capable of providing a detailed description of the individual choice process, but there were some questions as to whether or not it was amenable to travel diary data input which by the late 1980's was becoming accepted as a dominant and detailed form of obtaining information for models of activity scheduling and choice behavior (Gärling, Kwan and Golledge, 1994). The emphasis on this highly disaggregate base also raised questions as to whether or not output could be aggregated in order to provide some reasonable basis for forecasting and policy development. Two parallel alternative approaches have been suggested: microsimulation has been developed for forecasting from systems of disaggregate discrete choice models (e.g., Kitamura and Goulias, 1989) and combining CPM and discrete choice models in a single complementary context (Ettema, Borgers and Timmermans, 1993). In either case, one can argue that the intrinsic value of the CPM or production system approach would be to provide the theoretical basis for the microsimulation or CPM/discrete choice model approach. In the following sections, therefore, we will review a selection of Computational Process Models, discuss a recent contribution from geography which combines the Computational Process Model idea with a Geographical Information System (GISICAS) (Kwan, 1994, 1995), and comment on both the microsimulation and CPM plus discrete choice model combination approach.

2 Review Of Computational Process Models

One of the first attempts at developing a CPM of travel choices was that offered by Kuipers (1978) - the TOUR model. This focused on an individual's memory

representation of the environment (i.e., cognitive map), the acquisition of environmental information through search and exploration, and the use of experience and stored memories for making route choices. The model was developed in an artificial simulated environment and lacked empirical application using actual examples of cognitive maps, spatial orientation capabilities, and wayfinding procedures.

A similar type of model (NAVIGATOR) (Gopal, Klatzky and Smith, 1989; Gopal and Smith, 1990), is based more on the principles uncovered during empirical research on the spatial knowledge acquisition and wayfinding abilities of children traveling through a well known neighborhood (Golledge, Smith, Pellegrino, Doherty and Marshall, 1985). Using this practical knowledge base the route planning procedure in NAVIGATOR is modeled by various choice heuristics. When information for making this particular segment choice is lacking, a general route selection criteria such as "moving in the same general heading" or "make a random turn at an intersection" represent options for next segment selection in the path following process. Again, however, there was considerable input from prior empirical testing of human behavior in route selection tasks in a real environment, the model was still developed in a small hypothetical space.

Route following in a static environment is also the focus of another CPM, TRAVELLER (Leiser and Zilberschatz, 1989). An equivalent type of model in a dynamic environment was labeled ELMER (McCalla, Reid and Schneider, 1982). TRAVELLER simplifies the route selection problem by assuming that the relative locations of origins and destinations are known. This, of course, is perfectly reasonable in most routinized travel activities; it may not be quite so acceptable when we look at the question of deliberated choice where choosing a destination from a set of feasible options is part of the travel planning process. TRAVELLER then constructs a route from origin to destination via a process of search. In this case the production system consists of a set of rules which constrain how search and exploration can take place. In comparison to this the ELMER model conceives of routes as sequences of instructions for how to travel (e.g., go ahead 200 yards, turn right at the intersection). These instructions are retrieved when a particular need arises - for example when one must make a decision about a turn that could result in heading towards or away from a potential destination. Thus, route following is seen as a dynamic decision making process in which choices for segment selection and turns are made en route upon recall of appropriate constraining rules.

The above models, however, did not stress the dependence between travel choice and activity choice. CARLA (Jones, Dix, Clarke and Heggie, 1983) and STARCHILD (Recker et al., 1986a, 1986b) do attempt to address this problem. CARLA in general has the fewest behavioral assumptions but is tied more strongly to various time geographic concepts (e.g., Lenntorp, 1978). In particular it incorporates a variety of time geographic interaction constraints including

capability and coupling constraints. Its output consists of sets of feasible activity schedules and sets of possible activity patterns.

STARCHILD is a very comprehensive CPM and emphasizes modeling of the choice between activity schedules. It incorporates a conventional discrete choice model to make such selections, but the authors agree that other theoretically sound choice models could be appropriately substituted. The emphasis in STARCHILD is on the utilities associated with each activity and the sum of the utilities that comprises a particular schedule. Thus, utilities of waiting time and travel time are important features to consider. Perhaps the conceptually weakest part of STARCHILD is its acceptance of utility maximizing assumptions and its use of combinatorics to evaluate all possible feasible choice patterns. In practice, of course, people have limited capability both for considering a finite number of options and for accessing what is truly optimal. A boundedly rational selection mechanism could however be incorporated into STARCHILD thus bringing it much closer to the realities of human decision making.

In an attempt to incorporate more realistic behavioral assumptions and to begin the process of including a perceptually valid environment in the model, Gärling, Brännäs, Garvill, Golledge, Gopal, Holm and Lindberg (1989) outlined a conceptual framework which could be implemented into a model they called SCHEDULER. This model focuses on an individual's choice of activities, selects from feasible set of destinations, examines possible departure times which are critical in forming a travel agenda for a particular time period. Activities were generally stored in a long-term memory system called "the long term calendar." Associated with each activity is a priority for waiting time and a maximum duration for completing the activity. A specific activity is retrieved from long-term memory and scheduled on the basis of its relative priority weight and the expected duration required for its completion. Spatio-temporal constraints, including the hours of business and the determination of sets of reachable locations, are retrieved from a memory representation or stored cognitive map of the environment. This is obtained a priori and stored in long-term memory. Choice of the location of a feasible destination and a potential departure time is then determined by the SCHEDULER as it works in a top-down fashion scheduling the highest priority and most repetitive needs first. A possible activity schedule is stored in a short-term memory (the short-term calendar) for possible later execution, depending on whether or not critical input variables such as the duration of time allocated to the activity remain constant or are changed. In this model members of the feasible alternative set are evaluated according to a nearest neighbor heuristic (Hirtle and Gärling, 1992; Gärling and Gärling, 1988). Since in the SCHEDULER the constraints on when activities can be performed (e.g., open hours for business purposes) are part of the initial filtering process, the choice of a feasible location is at least partly determined by the duration allocated to the activity and business open hours during which the activity can be performed. If a possible sequence of activities is defined but cannot be executed because of a temporal overlap, the activity sequence is redefined by resolving

conflict among the competing activities. Here, higher priorities are given precedence. This conceptual model has been expanded by Kwan (1994, 1995) by hosting the scheduling module in a GIS context. We now explore this in more detail.

GISICAS represents an attempt to overcome some of the limitations of existing CPMs in terms of their lack of geoprocessing capabilities to handle the vast amount of real-world location and route data, and to perform spatial search using information about the objective and cognitive environments of the traveler. Although the scheduling algorithm of GISICAS benefited considerably from that of the SCHEDULER, it extended the framework of the SCHEDULER in several ways. Besides an individual's home and work locations, and the priority, duration and timing of activities, a person's preferred and fixed destinations were also included in GISICAS as important elements of the cognitive environment. The procedures of activity scheduling were integrated with a comprehensive geographic database of a real urban environment and interact dynamically with the module of spatial search heuristics in relation to that environment. Realizing the simplicity of the nearest neighbor heuristic used by the SCHEDULER, several new spatial search heuristics were developed in GISICAS for handling the effect of locational preference and the binding effect of fixed destination on an individual's travel behavior. Basically, they were high-order spatial search heuristics which, instead of looking for the nearest activity locations locally, search for globally satisficing locations in relations to the next fixed destination to which an individual has to travel to. GISICAS's procedure for delimiting the choice set in explicit spatial terms also represents a departure from the largely aspatial or pseudo-spatial method of the SCHEDULER. The concept of feasible opportunity set was first formulated by Golledge, Kwan and Gärling (1994) for expressing the effect of bounded rationality on the choice set and implementing the satisficing principle in explicit spatial terms. It was defined with respect to a person's home and work locations. In GISICAS the feasible opportunity set was defined dynamically with respect to the current location and the immediate spatio-temporal constraints of the traveler (e.g. time allowed for the activity and travel to the destination, distance willing to travel, etc.). This sequential identification of the choice set regarding feasible destinations enables the dynamic interaction of the planning and execution of the activity agenda. The focus of GISICAS on the spatial dimension of activity scheduling and travel decision making suggests an alternative way of modeling travel behavior at the individual level. With the data handling and geoprocessing capabilities of GIS, modeling and analysis of travel behavior does not depend on any prior schema of zonal division of the study area. This may open up a new arena for future research on the use of CPM in transportation science.

3 Micro Simulation Models

A modified form of the CPM has recently been developed by Ettema, et al. (1993) and Ettema, Borgers and Timmermans (1995). Like SCHEDULER, SMASH emulates the scheduling process by computing utilities for choices that result in inclusion, deletions, or substitution of activities. In this model, as the number of potential choices increase, disutility occurs. The decision making process is cumulative and it terminates when no choice results in a positive utility. The utilities associated with the choice of activities depend on the value of priorities for activities in the schedule, travel distance or travel time, the attractiveness of possible locations, the pressure on the individual to complete the activity within a certain time range, and the waiting time before the activity can be implemented and completed. Once a schedule is determined, its realism is evaluated. The SMASH model includes factors that can be assumed to effect activity scheduling and in some respects may be said to have similarities with STARCHILD. It appears to be a more complete model than SCHEDULER. However, whereas in STARCHILD utility maximization is an end product, in SMASH utilities are maximized at each step in the scheduling process. Thus, as each activity is evaluated for possible inclusion, deletion, or substitution in a schedule, the utilities associated with the appropriate process are assessed and ordered. It is thus a more disaggregate and implemented model than is STARCHILD and it raises the question as to global versus local maximization. Once again the original SMASH model required all possible choices to be evaluated at each scheduling step which would in reality place a considerable burden on the human traveler. Substituting a feasible opportunity set reduces the magnitude of this presumed computational component.

A significant added strength of SMASH, however, is that the authors have envisaged a way of empirically testing the model using mathematical statistical modeling (Ettema and Timmermans, 1993). The fundamental characteristics of this empirical testing focuses on the choice processes of including, deleting, or substituting activities. These actions are predicted from variables describing the current state of the scheduling process such as the number of activities already scheduled and attributes of the activities that still remain to be scheduled. While some inferences about these actions can be made from examining detailed travel diary records, the authors point out that there still remains much to be learned about the scheduling process itself. Particular items suggested for inclusion in future versions of the model include incorporation of mode choice, the planning of time spent at home, the addition of constraints and the sequence of activities so that some activities are not planned before undertaking others, and the linking of a production system to observe behavior so that specific parameter values can derived for the model and tested in different environmental, socio-economic, demographic, and mode choice mix environments. This would allow comparison of the outcomes of simulations of a selection of activity schedules using different parameter settings, with the observed scheduling behavior of humans. Extensive testing in this way should be able to provide a range of "best specification" for parameter values in different environments. As an alternative, parameter values

for the model could be collected during interactive simulations in which subjects would be required to complete a task consisting of a number of clearly specified steps that are part of the scheduling process. However, modeling each step separately could provide substantial problems in terms of integrating the results into a single final comprehensive model. At this stage, however, it appears that SMART, STARCHILD, and the SCHEDULER/GISICAS alternatives are equally feasible alternatives to further examine the process of activity scheduling and the act of tying together scheduling and travel behavior.

Epstein has built a pragmatic navigation model (Epstein, 1996). This model acquires facts about a two-dimensional environment in order to travel through it without an explicit map in its memory prior to travel. Spatial information is accumulated during travel which can be described as sequential trip-making through a fixed maze with specific barriers. Insights about basic points (landmarks), jagged or smooth barriers, bottlenecks, and other obstructions are learned during a sequence of trials. What is learned on one trial is stored and used to help make decisions on the next trial.

As with the other computational process type models previously discussed this device is tested in a simulated environment consisting of cells of a specific size (i.e., a grid network). The argument is that during experimentation individuals do not build detailed maps of the environment through which they wander but rather encode pragmatic representations of environmental features that assist in path-finding. In this type of world a robot or other traveling agent can learn it's way around in an efficient and effective manner. While doing so it creates a spatial representation consisting of selected parts of the environment and in some ways can be regarded as similar to the cognitive maps that humans would build in following the same set of tasks. These cognitive maps would be incomplete, in parts fuzzy, may not lend themselves to exact solution procedures such as minimizing distance or time. In some sense, therefore, the solution is a satisficing or perhaps boundedly rational one. A critical feature, however, is the limited nature of the space and it's dimensionality, but it is interesting to note that navigation can eventually take place in a rapid and effective manner even though the environment through which travel takes place is always a partially obstructed space. In the solution process, Epstein uses a "FORR" (FOr the Right Reasons) process. This type of program gradually acquires useful knowledge using a hierarchical reasoning process. It relies on different tiers of Advisors which are domain-specific but problem-class independent. They provide rational or support criteria for decision making (e.g., get closer to your destination). Each Advisor is implemented as a time-limited procedure and must operate within a constraint set which limits the number of permissible actions. Advisor recommendations are in the form of comments each of which has a weight, salience, or strength attached to it (i.e., an integer from 0 to 10 that measures the intensity and direction of the Advisor's opinion). Advisors usually do not recommend extensive search activities. Many of the Advisors embody within them the results of comprehensive spatial cognition work from recent decades. This includes advise

on alignment, direction of travel, orientation, navigating around obstacles, and neighborhood definition. The results of the application of the model would appear to have relevance for human navigation in that in general there is a tendency to select routes such that there are no substantial changes of direction during the wayfinding process; initially the strongest desire is to move toward the goal; travel is preferred along the main rather than orthogonal axes; there is a tendency to avoid neighborhoods with limited entrance and exit possibilities. On the whole, however, as with many of the other simulation models that could be found in the artificial intelligence literature, this is more a model for navigation and wayfinding than a model that explicitly attacks the question of activity scheduling and route selection in a spatial and temporal context that facilitates successful completion of an activity schedule.

Another computational process model recently developed is that by Chown, Kaplan, and Cortenkamp (1995). Chown, et al., offer a model called PLAN (Prototype, Location, and Associative Network model) which is an integrated representation of large scale space in which their claim is commensurate with a cognitive map. PLAN is used as a means for including wayfinding as a process which is concurrent with the rest of cognition not apart from it. The model is seeing-based because it takes advantage of the properties of the human visual system which provides continuous answers to the spatial updating or "where" problem. It synthesizes parts of prototype theory, associate network theory, and locational principles together in a connectionist system. The views in the PLAN model are not from an aerial or survey prospective but reflect what an observer would see from different head positions at a single location. This is similar in some ways to the model suggested by Golledge, Smith, Pellegrino, Gopal, Doherty, and Marshall (1985) which differentiates the environment into view (straight ahead linear observation) and scenes (more detailed local observations that might occur with head movements to the side as one is walking along a path). In the latter, views represent what might be seen when looking down the street into the distance, while scenes might be the explicit characteristics and features of a single house that would be observed if one turned their head from a facing direction while traveling. In the PLAN model, path overlap provides the mechanisms for developing new path segments which combine sections of previously experienced routes, and also provide the appropriate geometric base for integrating separate but partially overlapping paths into a more general knowledge of spatial layout (see also Golledge, Ruggles, Pellegrino, and Gale, 1993). Chown argues that a significant advantage of PLAN is that it only stores a fraction of the available information internally and relies on the perceptual system to fill in gaps when PLAN goes into action. This appears to be a reasonable way to operate a robot traveling through a learning environment but it also has some direct similarities concerning the way humans collect encode, store, and use information as they travel through complex environments. Particularly the idea of storing a minimal spatial representation as a cognitive map and perceptually updating one's location as travel takes place, represents a

reasonable wayfinding and search strategy for human behavior. PLAN thus responds to the criticisms of computational process models offered by Gärling, et al. (1989) who complained that an appropriate mix of attention paid to the processes of spatial cognition used by humans to extract and process information about environments as well as encapturing the essential components, barriers, and paths of the environment itself is required. The model GISICAS (Kwan, 1995) also takes these suggestions seriously and integrates cognitive processes, real-world environmental systems, and the intervening mechanisms associated with Geographic Information Systems (GIS) as a way of handling both wayfinding and activity scheduling problems in complex real-world systems.

4 Multi-Criterion Equilibrium Traffic Assignment Models

Multi-criterion equilibrium traffic assignment models developed in part because of a lack of attention to any realistic interpretation of the value of time problem in traffic assignment. Virtually every transportation model is ultimately evaluated in terms of how users interpret the value of time (VOT) that the model requires them to expend. This is true for mode choice models, congestion pricing models, and traffic assignment models. It is generally recognized that each individual has a different VOT depending on factors such as the person's economic resource base or the time that one is willing or able to spend on a trip. For the most part, transportation planning models acknowledge this by developing an average view of time figure and as a result they invariably produce large estimation errors and inaccurate forecasts. Recently, Ben-Akiva developed a logit mode choice model by assuming that there was a distribution of the value of time characteristics rather than assuming a similar VOT for all users. The result was a significant improvement of goodness-of-fit between predicted choices and actual choices. Dial (1995) consequently proposed a similar remedy for traffic assignment models. His model admits that VOT is best captured by a distribution and it uses a bi-criteria user optimal equilibrium traffic assignment model which generalizes classic traffic assignment by relaxing the VOT parameter in the generalized cross function from a constant to a random variable with an arbitrary probability density function (Dial, 1995). His model, called T2, is said to respond to a variety of difficult existing problems including the mode/route choice problem, parking policy, and congestion pricing. T2 models mode choice by assigning trips to paths in a multi-modal or hyper network. The latter combines walking, riding, transit and highway links. It is able to selectively route auto trips to parking lots that have a specific range of charges associated with them (cheaper lots that may require a longer walk to a destination), or to other higher priced lots that reduce the walking component of a multi-modal trip. It is also touted as being an appropriate model for determining where to place toll booths and what prices to levy in order to reduce congestion. In discussing his model, Dial captures some of the time/cost tradeoffs of a variety of different forms of transportation, but it

satisfies none of the behavioral criticisms levied against econometric and mathematically optimizing traffic assignment models.

T2 works as follows. Assume it is necessary to make a trip from an origin O to a destination D. The problem is to determine the mode choice for the trip. Dial first assumes that it is possible to enumerate all feasible paths for this trip and to know the time and cost of each path. Each path is then plotted at a point in a graph according to its time and cost. One might show fifteen feasible "paths" in terms of time and cost between a given O-D pair. Today, a helicopter is often the fastest mode and the most expensive while walking is the slowest and cheapest. Dial then examine the process of selecting among possible mode/cost/time possibilities. It develops a path-finding algorithm which examines all possible combinations of mode/time/cost and determines an optimum. In an argument similar to that used to determine feasible alternative destination sets from among all possible sets that was developed in SCHEDULER and GISICAS, Dial differentiates between mode/time/cost combinations by determining a likelihood that a particular combination will be chosen. In this way many potential combinations are eliminated and only those few feasible paths connecting a given origin and destination are examined. This final traffic assignment model accumulates trips for all O-D pairs and defines a user optimal traffic assignment. This solution is termed a traffic equilibrium, and focuses on the relationship between travel times, cost, and volume of flow along arcs of a given path.

This model is a return to the classical mathematical/econometric model of traffic assignment, and does not deal with travel behavior. It does make some concessions to the CPM and discrete choice related research which emphasized the significance of disaggregate units and individual differences in evaluating activity schedules and travel paths by including a value of time distribution characteristic rather than a single VOT estimate across an entire population. The question remains, however, whether it is suitable primarily for the routinized travel behaviors or whether it is robust and versatile enough to also incorporate path selection, mode choice, and travel behavior for the other activities we have previously described as resulting from deliberated considered choice, with conflicts being resolved in a dynamic on-route environment.

5 Summary And Discussion

In this paper we have reviewed and assessed a variety of approaches to the activity scheduling and travel behavior problem. Among these were a range of computational process models and some recently emerging alternatives including microsimulation, multicriterion traffic assignment models, and combined CPM/discrete choice models. Of this set we have argued that the CPM approach allows one to move closest to the real world decision making and choice situation and allows us to incorporate elements of both objective and cognitive environments as the matrix on which activity schedules and travel choices are

made. For traffic assignment in a multimode environment, the T2 model appears to have significant promise. Of the various CPMs reviewed, SMASH and GISICAS both appear to be flexible, expandable, developed at the individual level but capable of aggregation, and suited for testing in real world environments. STARCHILD also has been tested on real world travel diary data with considerable success. It is quite possible that with some modifications such as the inclusion of a procedure for determining feasible alternative sets rather than going through complete enumeration of all possible activities, embedding the model in a Geographic Information System in a real-world environment, and allowing a boundedly rational selection criteria to replace the simple maximizing utility assumption, then STARCHILD could be expected to achieve a considerable success at predicting and forecasting travel behavior. Of the models examined, SMASH attempts to integrate the recent CPM approach with the more traditional discrete choice model approach and by combining the most powerful aspects of each, provides significant hope for successful application - which application appears to have recently been completed (Ettema, 1995).

In order to continue evaluating and assessing the different avenues of current research, specific empirical testing will be required. This requires explicit testing of the behavioral assumptions entailed by the different models as well as by assessing their ability to consider different mode combinations, and different combinations of activities in a schedule. GISICAS argues that scheduling must take place over a longer period than a day for some high priority activities (e.g., food shopping) may only be undertaken every second or third day. At that time, however, their importance is extremely great and scheduling must be adapted to allow the activity to take place.

The increasing volume of travel diary, panel, and survey data is providing more and more insights into the process of travel behavior and mode choice. However, detailed testing of how activities are selected and how the selections are combined into schedules is still a critical point for future research. GISICAS is the only model so far to explicitly incorporate a Geographic Information System (GIS) into its structure. Obviously the potential for GIS must be further examined. This examination should include the suitability of GIS as a host for recording diary, panel or survey data, as well as its potential for developing an interactive framework for the assessment of priorities associated with activities and the choice of an appropriate path selection model. As far as the latter is concerned, more work needs to be done on the criteria that can conceivably be used in the path selection process. All too often assumptions are readily accepted that minimizing distance or minimizing time or cost are the only criteria worth considering. Recent research (Golledge, 1995a and 1995b; Kwan, 1994) has indicated that there are a number of other feasible path selection criteria and spatial search heuristics that may have to be made available in a group of models that could potentially be used in successful path selection and travel behavior prediction. A GIS seems to be a reasonable host for incorporating a variety of models which can satisfy criteria such as minimizing turns, always heading in the

direction of your destination, selecting the longest or shortest leg first, maximizing the aesthetic value of the route, minimizing perceived or actual costs, minimizing perceived or actual distance, minimizing perceived or actual time. Most model frameworks adopt one or another of these path selection criteria in their trip behavior phase. It appears that different criteria may well be used for different trip purposes. If this is the case then standard models based on single criteria cannot possibly hope to satisfactorily forecast travel behavior. A GIS that includes a set of path selection algorithms which could be initiated by a predisposition of a traveler to select certain criteria for certain purposes, could add significantly to our ability to understand and perhaps even to forecast the complex set of trips that make up the activity patterns of population aggregates. It is our intention in the future to continue working on these problems and, in particular, to determine the type of GIS (e.g., object oriented or relational) that will best lend itself to the procedures defined above.

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