Title
The Potential for Integrating GIS in Activity-Based Forecasting Models

Author
McNally, Michael G.

Publication Date
1997-06-01

UCI-ITS-AS-WP-97-3

The Potential for Integrating GIS in Activity Based Forecasting Models

Michael G. McNally [1]

UCI-ITS-AS-WP-97-3

[1] Institute of Transportation Studies and Department of Civil and Environmental Engineering
University of California, Irvine; Irvine, CA 92697-3600, U.S.A., mmcnally@its.uci.edu

June 1997

Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.

A preliminary version of this paper was presented at the NCGIA I-10 meeting, "The Relationship between GIS and Disaggregate Individual and Behavior Transportation Modeling", University of California, Santa Barbara, June 7-8, 1996

The Potential for Integrating GIS in Activity-based Forecasting Models

Michael G. McNally
Institute of Transportation Studies and
Department of Civil and Environmental Engineering
University of California, Irvine
Irvine, CA 92697-3600
Tel:949-824-8462
Fax:949-824-8385
E-m:mmcnally@uci.edu

Abstract

An increased interest in the development and implementation of activity-based modeling approaches has been evident in the ISTEA era given federal mandates to improve current modeling practice. Several activity-based alternatives to conventional regional forecasting models are presented. Each of these approaches integrates household activities, land use distributions, regional demographics, and transportation networks in a framework which explicitly recognizes the complexity of travel behavior in terms of spatial and temporal constraints, household interactions, transport accessibility, and its inherent activity-derived basis. A brief evaluation of the temporal stability of the proposed basic unit of analysis, the household's set of individual activity patterns, leads to s summary of a pattern-based generation model and the initial development of an activity-based microsimulation to replace the demand components of the conventional process.

Presented at the NCGIA I-10 Meeting
"The Relationship between GIS and Disaggregate Individual and
Behavioral Transportation Modeling"
UCSB, Santa Barbara, CA USA, June 7-8, 1996.

1. OVERVIEW

The conventional model for travel demand forecasting, in use for several decades, has undergone very few substantial changes during that period. Not only does the basic four-step model remain the status quo, but pre- and post-analysis have evolved little as well. Disaggregate choice models and equilibrium assignment procedures have been introduced, but the overall structural sequence has been maintained. Also, the potential benefits offered by these advances have been limited by their application in the last half of the model's functional sequence. Some advances have been made in developing the comprehensive data required by these models, but these advances have neither been integrated into the model structure nor significantly altered the capabilities to assess alternate policies. Axhausen (1996) states that "transportation demand models...have...remained roughly as complex as the policies they were designed to evaluate". It is the complexity in the travel behavior that these policies seek to influence that presents the current challenge for improved forecasting procedures.

The various deficiencies associated with the model have been often noted and at times considered in depth, but no recipes for remediation have been offered. Furthermore, despite the wealth of literature scrutinizing the model system, even critics seem to agree that it was designed to evaluate major infrastructure changes and has accomplished this task with some measure of success. These and a variety of institutional factors have set the modeling procedures in the same concrete as the infrastructure being modeled.

Transportation is inherently a temporally and spatially defined activity, but both these dimensions have been trivialized in theory and practice. Trips are generated by a household as a function of only that household's demographics, not as a function of the relative opportunities in space. When trips ends are paired in distribution models, no other trip linkages are considered until aggregate splits are applied to convert productions and attractions to origins and destinations. Aggregate distributions are again introduced late in the model sequence to reflect trips in motion, with no attempt to reflect the dynamics of activity scheduling. Virtually all conventional assignment models are static, with each single vehicle simultaneously appear on every link of its path, violating any reasonable view of space-time.

Although applications of GIS have been more prevalent in the transportation field, its use in travel forecasting has been extremely limited, particularly as a fundamental, integrated component. Most forecasting projects are dependent on standard modeling software packages, few which are readily compatible with GIS. The intent of this paper is to present activity-based alternatives to conventional models that explicitly integrate GIS in model application, if not as a fundamental model component. After a review of modeling alternatives and data considerations, several applications of activity-based models with integrated GIS are presented. Some directions for the continued development and application of these models and an assessment of future data needs and of potential GIS roles conclude the paper.

2. CONVENTIONAL AND ACTIVITY-BASED APPROACHES TO FORECASTING

It is accepted that travel, in theory, is derived from the demand for activity participation; in practice, however, it has been modeled with trip-based rather than activity-based methods. The inadequacies of the conventional transportation demand modeling process are well documented (McNally and Recker, 1987). Over the last five years, significant federal funding has been directed toward the Transportation Modeling Improvement Program (TMIP), a multi-track effort to increase the policy sensitivity of travel forecasting procedures. The current modeling process, referred to as the four-step process, may be viewed in two stages. In the first stage, traveler, network, and activity system characteristics are "evaluated, calibrated, and validated" to produce a non-equilibrated measure of travel demand. In the second stage, this demand is loaded onto the transportation network in a process that amounts to the static equilibration of route choice only, not of other choice dimensions such as destination, mode, time-of-day, or whether to travel at all. This approach has been moderately successful in the aggregate, but it has failed to perform in most relevant policy tests.

The activity-based approach, which has been forwarded over the past fifteen years, provides a comprehensive framework to resolve some of these issues (McNally and Recker, 1987; Axhausen and Garling, 1992; Pas et al., 1994). A brief comparison of the conventional model and activity-based approaches is provided by McNally (1997):

Characteristics of Activity-based Approaches

1. travel demand is derived from activity participation
2. activity participation involves generation, spatial choice, and scheduling
3. activity and travel behavior is delimited (or even defined) by constraints
4. linkages exist between activities, locations, times, and individuals
5. alternate decision paradigms are probable

Characteristics of the Convention Modeling Process

1. trip-based versus activity-based
2. un-linked daily household trip generation rates applied with zonal demographics to expand to zonal trip-ends
3. distribution of un-linked trip ends accomplished via aggregate interaction models with general network impedances
4. conventional 4-step process models network-level traffic effects via static assignment
5. all disaggregate spatial and temporal information (chaining and time-of-day) is lost

The state-of-the-art in activity-based approaches has advanced to the point where integrated model systems which can address the shortcomings of the conventional process are now under development. Current forecasting models are applied sequentially; as such, the first stage, trip generation, greatly defines potential model performance. Despite the recognized importance of accessibility and level-of-service, these characteristics are completely absent from current trip generation models. This shortcoming is in part due to the complexity of travel behavior and in part to the complexity of the modeling process itself. The initial application of activity-based approaches will consider an alternative to trip generation and the integration of this alternative into both the conventional and innovative forecasting models.

3. DATA

For a process remarkably dependent on and driven by data, travel demand forecasting has been characterized by an equally remarkable lack of consistency, compatibility, and comprehensiveness in data structures. The sheer complexity of transportation data, the breadth of data types and sources, and the specific demands of different model software packages are but a few of the contributing factors to this problem.

Most major US metropolitan areas have competed major travel surveys in the past ten years (Cambridge Systematics, 1996), however, even among those areas who have formally addressed data problems in general and survey needs in particular, few advances have been realized in improving data structures. One advances explicitly tied to activity-based approaches in the use of activity diaries in lieu of conventional travel diaries. The major contribution of this change is a reduction in reporting errors, but essentially the same information is gathered and, to a large degree, the same information not gathered before is still left out of the survey instruments. A case in point is constraint information. Hagerstrand's (1973) original formulation of activity participation in space and time was explicitly constraint driven but virtually all current surveys gather information only on revealed (and sometimes stated) preferences. To what degree any travel or participation decision is choice- or constraint-based must be assumed. Axhausen (1997) provides a summary of the relevant data issues in activity-based models.

To what degree GIS can resolve these data problems is a question being currently addressed. In the three sample applications that follow, a GIS is used in a conventional mode for data management and visualization. Basically, the GIS provides an effective tool to achieve a defined goal where other albeit less effective tools were available. In the third application, however, the GIS becomes a fundamental component in the model structure, providing the representation of space in an inherently spatial framework.

4. APPLICATIONS

To illustrate the potential utility of activity-based approaches as alternate paradigms to conventional models for travel forecasting, some of the concepts presented above are subject to empirical tests. The primary objective is to present new travel forecasting models integrated with a GIS, that is, where the GIS becomes a fundamental component in the model's structure. The GIS package utilized, TransCAD (Caliper, 1996) provides perhaps the only conventional travel demand forecasting package fully integrated with a GIS. While the selected activity-based approaches might well be implemented with other GIS platforms, TransCAD was selected to facilitate comparison with conventional models.

The central tenet of these applications is that the household's daily activity patterns represents a fundamental structure upon which travel models can be calibrated and used in forecasting. While there is no general agreement that this static representation of an activity pattern should serve as the fundamental structure, it should be noted that any components of these patterns, whether trip chains, activity sequences, or other convenient units, could equally well serve in place of the full pattern. Furthermore, the potential to construct these patterns dynamically is inherent in the model structure.

After a brief presentation of the data used in these applications, the issue of temporal stability of activity patterns is addressed. This is followed by a summary of an activity-based generation model which serves as an alternative to trip generation in the convention model system. This model is then introduced as the first component of a GIS-based microsimulation model for forecasting activity patterns. The initial phase of that microsimulation model is presented with a brief discussion of work in progress.

4.1 Activity Data

The data utilized in this analysis included the Orange County sub-samples of the 1976 and 1991 Southern California Association of Governments (SCAG) Regional Origin-Destination Surveys, Census Tiger files and tract demographics for Orange County, transportation networks and models from the Orange County Transportation Analysis Model (OCTAM), and an ARC/INFO land use database from the Orange County Administration Office. The Orange County sub-sample of the SCAG Survey includes a 24-hour travel-activity diary for each member of selected households as well as conventional socio-economic characteristics of individuals and their household. The sample drawn from the 1976 survey contained 665 individuals in 249 household in the developed portions of norther and central Orange County, California. Gender was equally split, 38 percent of the individuals were employed full-time, and 35 percent were children. The sample drawn from the 1991 survey contained 464 individuals residing in the same areas of the county. Gender was again equally split, however, 49 percent of this sample were employed full-time and only 20 percent were children.

4.2 Investigations of Pattern Temporal Stability

The product of conventional trip generation modeling, household trip rates, have been shown to be fairly stable over time when controlling for basic socio-economic variations (e.g., the effects of income, household size, car ownership). Although a pattern-based versus trip-based model would be beneficial from a theoretical perspective, practical application of the resulting model would be constrained if temporal stability was limited or absent. It is not clear at which level stability should be defined. In parallel to the aggregate full pattern approach, it may useful to investigate the stability of trip chains using these data sets. Chains are identified referenced to the full pattern in which they occur; activities are referenced to the chain and the full pattern.

A multi-attribute classification of observed daily activity patterns via discrete time slices leads to the identification of Representative Activity Patterns, or RAPs, for population segments with similar pattern attributes. These identified representative patterns may then be related to demographic, land use, and network characteristics for application in micro-simulation or general policy analysis models.

Generation of Representative Patterns

Following the classification methodology applied to the 1976 data (Recker et al., 1985), attribute data was prepared for 128 time slices between 5:30 AM and 12:30 AM (19 hours). The first attribute developed, distance from home, was an attempt to collapse space into a single dimension. For each individual pattern, all destinations were plotted using TransCAD and Euclidean distances were computed. The second attribute developed, activity type, was an attempt to capture the nature of the activity, a nominal variable, with an interval scale. Home activities and travel were placed on opposite ends of the scale with work at the midpoint. Other activity types were scaled to maximize separation between dissimilar activities (see Recker et al., 1983). The transformation procedures applied to the 1976 data were not necessary with the 1991 data. The matrix of pattern attributes by time slice was cluster analyzed via a modified K-means algorithm to produce the final classification results.

The direct outputs of the classification algorithm are centroids of the pattern clusters; these centroids each comprise an activity image and distance-from-home image, specified by time-of-day (each classification attribute produces a temporal vector of representative values). Underlying distributions of other characteristics, such as activity and travel frequencies, are developed for all patterns in each cluster. This information taken as a whole defines a Representative Activity Pattern (RAP). To facilitate interpretation, a fully specified pattern corresponding to the RAP may be synthesized; alternately, the observed pattern closest to the RAP centroid may be selected as "representative" of the RAP. Finally, the demographics (and other household and individual attributes) corresponding to each RAP may be tabulated. A modified version of the original classification algorithm used on the 1976 data was applied to the 1991 sample. After removing a small number of data outliers from each data set, both the 1976 and the 1991 data produced eight RAPs.

Comparison of 1976 and 1991 RAPs

While there are many potential metrics by which to assess goodness of fit between those RAPs generated for 1991 versus those generated for 1976, the comparison here is restricted to a subjective evaluation of similarity using the original classification variables, underlying travel characteristics, and the associated demographic profiles. Eight comparisons are presented.

Comparison 1. 1991 RAP 1 (n=23) versus 1976 RAP B (n=56)
Each RAP was associated with employed adults (70 percent male) executing a traditional work day comprising an AM-peak commute to a conventional work activity (8 miles from home on average),

some noon-time activity, and a return home trip in the PM-peak. These RAPs each also exhibited some evening social or recreational activity and some degree of trip chaining with an average of 4-5 trips in the patterns. RAP similarity was considered very good.

Comparison 2. 1991 RAP 2 (n=161) versus 1976 RAP H (n=62)
Each of these RAPs were similar to the Comparison 1 RAPs. These individuals were employed adults (half male) executing an AM-peak commute (but with later departure times, on average) to a work location (8 miles from home on average), some noon-time activity, and a return home trip in the later PM-peak. These RAPs did not exhibit any evening non-home activity and had an average of 3-4 trips per pattern. RAP similarity was considered very good.

Comparison 3. 1991 RAP 3 (n=8) versus 1976 RAP F (n=13)
These RAPs, each with few observations, exhibited great similarity. The initial home departure was late (9:30 or later, on average) to work and other activities which were fairly close to home. Most individuals were engaged in some non-home activity by mid-afternoon at, on average, seven miles from home, followed by additional non-home activity (primarily social/recreational) after 9:00 pm. Only half return home by 12:30 am. The 4 trips per day average exhibited significant trip chaining. These individuals were employed younger and middle aged adults in 1976 and employed older and senior adults in 1991. With the assumption of cohort aging, this represents an excellent RAP match over the 15 year time interval.

Comparison 4. 1991 RAP 4 (n=24) versus 1976 RAP C (n=82)
Each RAP exhibits an early AM-peak home departure to either work or school activities with a seven hour average activity duration, but with a significant difference in activity location (an average of 7 miles in 1991 versus only 3 miles in 1976). Each RAP also tends to exhibit late afternoon and early evening non-work activity and travel, on average 4 miles from home. The final return home trip averaged 10:00 pm. Greater than average trip chaining was evident, with over 4 trips per day on average. The ratio of employed adults to school children was about 2 to 1 in 1991, but closer to the reverse in 1976 (which may account for the lower work/school distances). The activity match was very good; distances provided a reasonable match.

Comparison 5. 1991 RAP 5 (n=31) versus 1976 RAP E (n=47)
Early AM travel and activity characterize these RAPs. Significant differences exist between these groups in both average distance from home and activity type between 8:00 am and 4:30 pm where the 1976 RAP has predominantly work activity farther from home than the work and non-work activities in the same time period in 1991. Both RAPs do exhibit PM-peak travel and evening activity of various types (all returning home by 11:00 pm). Average trip rates were high (5 trips per day per person). The 1976 individuals were predominantly employed males whereas the 1991 group was half female (half of them employed). Overall, these cannot be considered comparable RAPs.

Comparison 6. 1991 RAP 6 (n=110) versus 1976 RAP D (n=66)
Comprising primarily adult females (some employed), each of these RAPs exhibited various non-

work activities between 9:00 am and 5:00 pm within approximately 3 miles of home, with some evening activity and 4 trips per day, on average. Although the similarity of both distance and activity profiles was excellent, these RAPs are difficult to precisely define due to the variability in scheduling of short duration, flexible, non-work activities.

Comparison 7. RAP 7 (n=94) versus 1976 RAP G (n=305)
These RAPS were each characterized by a conventional school (some work) activity with an early AM-peak commute, an average six to seven hour duration, and a three mile distance from home. There was also late afternoon school or work activity at similar distances to home (3 miles), no evening activity, and a low average trip rate of 3 trip per day with some trip chaining. The activity and distance profiles, and the associated demographics, were considered a very good match.

Comparison 8. 1991 RAP 8 (n=12) versus 1976 RAP A (n=33)
Although each RAP was characterized by an early AM-peak commute to work activities, the averaged distance from home in the morning was less than in the afternoon in the 1991 RAP, perhaps due to multiple or part-time employment effects. However, the 1976 RAP exhibited significantly longer commute distances (30 versus 10 miles). For both RAPs, the return home was executed prior to the PM-peak and little evening non-home activity was evident. A low average of 3 trips per day per person exists for each RAP. These RAPs, each associated with employed adults, matched well on the activity type dimension but poorly on the distance from home dimension.

The resulting RAPs for Comparisons 1, 2, and 3 are displayed in Figure 1, 2, and 3.

Discussions and Limitations

If some measure of complex behavior is to be used in forecasting models, then the temporal stability of such measures must be established, in the same manner as in the conventional model where household trip rates categorized by socio-demographics have been shown to be stable over time. With the assumption that the daily activity patterns within a household can be used as such a measure in forecasting, the stability of these patterns must be assessed over time intervals representative of those used in forecasting models. Household travel diaries from 1991 were selected from the same areas of Orange County used in the 1976 classification exercise. The original map of 1976 trip ends was used to located the grid elements where these households were located. This grid was superimposed on the 1991 GIS file to extract a similar sample of households from the same areas. No attempt was made to replicate any characteristics of the original households. It is also recognized that significant changes have occurred in that area over the intervening 15 years.

The comparison provided is clearly subjective but nonetheless provides evidence of similarity in daily activity patterns over time. The 1976 pattern classification process entailed data transformation both prior to and after classification, resulting in a loss of some information (see Recker et al., 1983). Since the 1976 data was no longer available for analysis, the restrictions imposed on the original analyses were also imposed on that for the 1991 data, with the sole exception of the need to transform the original data for classification (since there was no longer computational and memory restrictions). It should also be noted that individuals who did not travel were not included in either the 1976 or the 1991 samples.

The temporal frequency distributions were not computed for the 1976 data, thus, it was difficult to assess the distance and activity type profiles to identify the relative proportions of individuals engaged in non-home activity at one specific time. It was also clear that increasing the number of classification attributes would have facilitated RAP identification and description (the attribute restriction was also an artifact of the transformation technique). A separation of the activity dimension into attributes defining travel, non-home activity, and activity type would have been introduced if the 1976 analysis could have been repeated.

4.3 An Activity-based Generation Model

In conventional travel demand modeling, trip generation is the first step and serves to estimate the intensity of travel demand. Trips are categorized by the inherent nature of the trip ends as either productions or attractions, and are presented as zonal or, more commonly, household rates. Regression and category analyses are two common methods used in modeling trip generation. The former method relates trip productions (or attractions) to zonal or household socio-economic characteristics via a linear compensatory model structure; model parameters are estimated via least squares or maximum likelihood techniques. The latter method uses a cross-classification technique to create relatively homogeneous groups based on these socio-economic characteristics; average trip rates are then computed for each group using observed data. These approaches deal separately with each end of an observed trip. The production and attraction ends of each trip are split and aggregated, parameters are estimated via independent models, and the basic unit of travel, the trip, does not again exist as a interconnected entity until the second phase of the standard forecasting process, trip distribution, produces aggregate estimates of total interzonal travel. It is only at this stage that any realistic measure of level-of-service can be introduced. These models explicitly ignore the spatial and temporal inter-connectivity inherent in household travel behavior. The fundamental tenet that travel is a demand derived from the demand for activity participation is explicitly ignored.

A alternate methodology for household trip generation is presented which is inherently activity-based. The spatial and temporal dimensions are implicitly incorporated, and the effects of household interaction and lifestyle on the travel pattern are captured. This model is directly reducible to conventional trip generation models, and can be substituted for these conventional models in the standard forecasting process. More importantly, this model serves as the initial component of an activity-based microsimulation model designed to replace the entire conventional model system.

The product of conventional trip generation modeling, household trip rates, have been shown to be fairly stable over time when controlling for basic socio-economic variations (e.g., the effects of income, household size, car ownership). Although a pattern-based versus trip-based model would be beneficial from a theoretical perspective, practical application of the resulting model would be constrained if temporal stability was limited or absent. Preliminary evidence of temporal stability was presented above. Wang (1996) has completed a more comprehensive study of temporal stability using activity diaries from Portland for 1985 and 1994. This work also presents an activity-based generation model.

Households in each of the two Portland data sets were segmented into six pre-defined life cycle groups; to illustrate this process, single parent households are selected. The stability analysis showed that the three representative activity patterns associated with this life cycle group in 1994 mapped extremely well into the fours RAPs identified in the 1985 data, with one 1994 RAP combining characteristics of two similar RAPs from 1985. Table 1 presents the corresponding pattern generation model for the adult only in single parent households. Note that a fourth pattern option, no travel, was present in the data but not part of the classification procedure. The model is a cross classification table with cars per household and employment status defining the cells. Also provided are standard trip generation rates (but her expressed for the adult only, since children in these households are treated independently). Captured in each potential pattern is the full spectrun of underlying activity scheduling attributes which can be utilized in any subsequent processing; alternatively, the model reduces to a standard trip generation model.

A alternate methodology for household trip generation has been presented which is inherently activity-based. The spatial and temporal dimensions are implicitly incorporated, and the effects of household interaction and lifestyle on the travel pattern are captured. This model is directly reducible to conventional trip generation models, and serves to replace these conventional models in the standard forecasting process. The model thus serves as the initial component of an activity-based microsimulation model designed to replace the entire conventional model system.

4.4 A GIS-based Microsimulation Model

Patterns identified in the generation component serve as seeds for synthesizing population patterns. The population distribution of similar households throughout the selected study area is utilized (based on census and other local data) to simulate the most likely activity pattern of each additional individual. This process assumes that the population-level representative patterns do indeed reflect underlying behavior, and that these patterns can be accurately associated with traveler characteristics; these assumptions have been tested and verified in earlier work (see Recker et al., 1985).

The general outline for pattern synthesis is as follows. The aggregate classification produces activity patterns which are specified by time-of-day in terms of activity type and distance from home (temporal information and activity sequencing are implicit). The classification also provides a probability distribution of activity type, mode, duration, and other attributes needed for activity scheduling. A household is selected and, based on demographic, land use, and network characteristics provided by the GIS, a target representative activity pattern is also specified. With initial parameters such as activity, mode, and start time drawn from the distributions associated with the target pattern, a trip is simulated based on a Monte Carlo approach of potential activity-specific destinations within a range of travel times from the current location. The GIS provides the ambient density of potential activity locations, depending on the current location, the transportation network for the mode being utilized, and the specific activity being simulated. As one of several control variables, the average distance from the home location for the target representative pattern is maintained to ensure that subsequent activity simulation will reflect the underlying representative pattern. After a destination and activity duration is determined, a second set of parameters is sampled, and a second activity is simulated based on the activity distribution and network characteristics relative to the prior destination. This process continues until the entire patterns is specified. The nature of the simulation is such that the simulated pattern, while maintaining the general characteristics of the target representative pattern, reflects the activity distributions and network characteristics of the household being analyzed as well as the underlying variability in activity frequency and scheduling. The output of this process are population level activity patterns, in theory equivalent to a population sample of any size. From these data, dynamic origin-destination matrices may be directly generated.

A sample application is depicted in Figure 4 and Figure 5. In Figure 4, a household was selected for a defined location and, based on that household's demographic profile, a target representative activity pattern is selected for each individual in the household (see the previous section for a sample of this generation model). For the activity being simulated, the relevant distance criteria are applied identifying ten possible destinations zones. In Figure 5, each of these zones has a relative probability of being selected based on the underlying distribution of criterion variables (in this case, employment) in the zones which fulfilled the distance criteria. The siimulation randomly selects a destination and proceeds with activity scheduling for the remainder of the pattern.

5. SUMMARY AND RESEARCH DIRECTIONS

A growing body of activity-based research has utilized structural equation models (SEM) (see Golob and McNally, 1997) to uncover fundamental interrelationships among the variables that influence activity participation and travel. Despite their utility in investigating feedback and other dynamic effects, SEM has exhibited little or no success in capturing the relative effects of space on activities and travel. The Household Activity Pattern Problem (HAPP), an alternative to the microsimulation approach, is a mathematical programming formulation proposed by Recker (1985) that has also had limited success in introducing spatial considerations. To what degree these limitations are defined by the complexity of the problem and to what degree integration of these model constructs in a GIS platform could facilitate problem resolution are questions left to future research. Results of SEM research, as well as results from a variety of other activity-based approaches, will in part influence the design of certain components of the GIS-based microsimulation. As theoretical advances are supported by growing empirical evidence, the associated models can replace the corresponding simulation structures in the microsimulation.

The role of intervening opportunities in destination choice is being investigated. Between anchors in an activity pattern (e.g., work, home), other activities often occur. While common sense dictates that additional activities arise when the opportunity presents itself (performing an unplanned activity when its activity location "intervenes" on the path to a planned activity), it is unclear under what situations this will occur (e.g., before or after anchor activities, in what types of chains defined by other activities and durations). An activity-based forecasting model integrated on a GIS-platform provides an excellent environment in which to conduct these tests.

A summary of Phase II of the microsimulation can be found elsewhere (McNally, 1997). There are several parallel research efforts underway, including TRANSIMS and AMOS (see Spear, 1994, for a summary). The status of aggregate model components (such as in Phase II), although clearly critical to the forecasting success of any alternate model structure, has not been yet well-established. The focus of the proposed microsimulation model is to provide a substitute for the generation and distribution components of the current model system rather than a complete system redefinition. If successful, these Phase I components are designed to be integrated into existing models, including the standard four-step process.

The implications for travel behavior modeling in general, and for trip generation and the remainder of the standard forecasting process, are significant. The questions asked were "can the complexities inherent in activity scheduling be captured via an activity-based modeling approach" and, if so, "is there sufficient stability in observed complex behavior (as there is in conventional trip generation) to warrant development of these techniques.

The availability of multiple data sets from two regions enabled temporal stability to be assessed. In both cases, evidence strongly suggests that travel behavior defined in complex terms (such as individual and household travel/activity patterns) is relatively stable over 10-15 year periods. Given this stability, a prototype activity-based travel/activity generation model was developed which subsumes conventional generation concepts while adding the capability to reflect the temporal and spatial connectivity in travel behavior which is absent in all current models.

ACKNOWLEDGEMENTS

This research was supported in part by the US Department of Transportation and the California Department of Transportation through grants to the University of California Transportation Center. The author thanks Ruey-min Wang and Anup Kulkarni for their contribution to the initial research summarized in this paper.

REFERENCES

Axhausen,KW (1997). *Data Needs of Activity Scheduling Models*, in Ettema,DF and Timmermans, HJP (eds.) **Activity-based Approaches to Travel Analysis**, Elsevier Science Ltd., Oxford.

Axhausen,KW and Garling,T (1992). Activity-based approaches to travel analysis: conceptual frameworks, models, and research problems, *Transportation Reviews*, 12(4), 323-341.

Caliper (1996). TransCAD User's Guide, Version 3.0 for Wwindows. Newton, MA.

Cambridge Systematics, Inc. (1996). Scan of recent Travel Surveys. Report DOT-T-97-08 prepared for the US Department of Transportation, Washington, DC.

Golob,TF and McNally,MG (1997). A Model of Activity Participation and Travel Interactions between Household Heads, *Transportation Research B*, 31,3,177-194.

Hagerstrand,T (1970). What About People in Regional Science? *Pap. of the Reg.Sc.Assoc.*, 23, 7-21.

McNally,MG (1997). *An Activity-based Microsimulation Model for Travel Demand Forecasting*, in Ettema,DF and Timmermans, HJP (eds.) **Activity-based Approaches to Travel Analysis**, Elsevier Science Ltd., Oxford.

McNally,MG and Recker,W (1987). *On the Formation of Household Travel-Activity Patterns: A Simulation Approach*, Final Report, USDOT, Washington,DC.

Pas,E, Kitamura,R, and Lula,C (1994). AMOS: An activity-based, flexible and truly behavioral tool for evaluation of TDM measures, presented at the 73rd annual TRB meeting at Washington, DC

Recker,WW (1995). The household activity pattern program (HAPP): general formulation and solution, *Transportation Research B*, 29B(1), 61-77.

Recker,WW, McNally,MG, and Root,GS (1985). Travel activity analysis: Pattern recognition, classification, and interpretation," *Transportation Research*, 19A, 279-296.

Recker,W, Root,G, and McNally,M (1983). *An Empirical Analysis of Household Activity Patterns*, Final Report, US Department of Transportation, DOT/RSPA/DMA-50/83/19.

Spear,BD (1994). *New Approaches to Travel Forecasting Models: A Synthesis of Four Research Proposals*, Final Report DOT-T-94-15, USDOT.

Wang, R-M (1996). An Activity-based Trip Generation Model. Ph.D. dissertation. Department of Civil and Environmental Engineering, University of California, Irvine.

Table 1. An Activity-based Pattern Generation Model: Adults in Single Parent Households (Portland 1994)

Adult Employment Status	Cars per hoousehold		
	0	1	2 or more
Employed	(Observed N= 5) Pattern 2A (0%) Pattern 2B (20%) Pattern 2C (20%) No Travel: (60%) Trips/adult = 1.75	(Observed N=34) Pattern 2A (20%) Pattern 2B (20%) Pattern 2C (56%) No Travel: (3%) Trips/adult = 4.13	(Observed N=32) Pattern 2A (5%) Pattern 2B (20%) Pattern 2C (70%) No Travel: (5%) Trips/adult = 4.04
Not Employed	(Observed N=9) Pattern 2A (0%) Pattern 2B (45%) Pattern 2C (45%) No Travel: (10%) Trips/adult = 3.97	(Observed N=10) Pattern 2A (20%) Pattern 2B (60%) Pattern 2C (0%) No Travel: (20%) Trips/adult = 3.79	(Observed N=3) Pattern 2A (0%) Pattern 2B (67%) Pattern 2C (0%) No Travel: (33%) Trips/adult = 3.21

LIST OF FIGURES

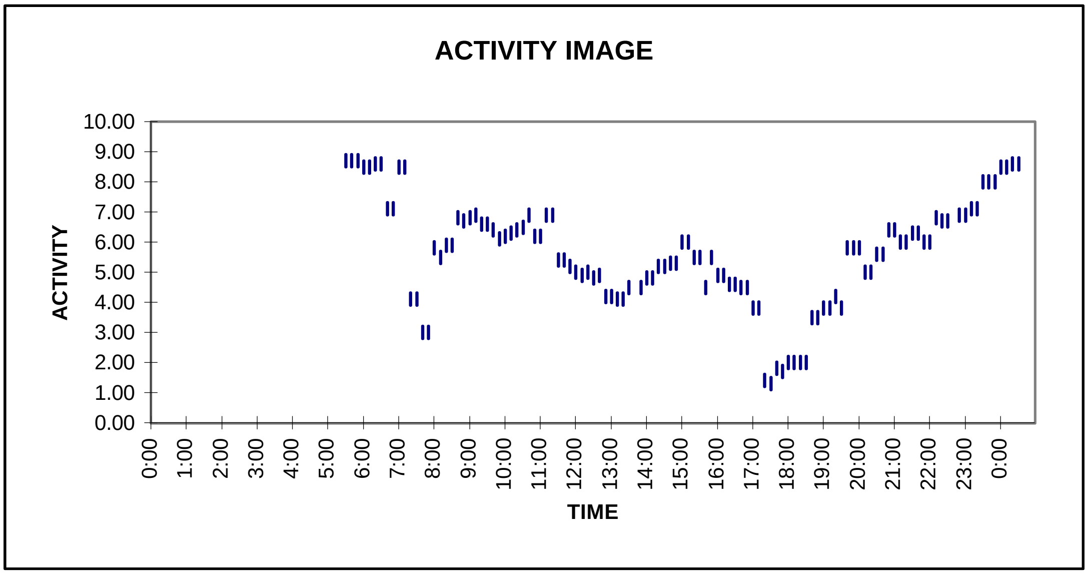
Figure 1A. 1976 SCAG Representative Activity Pattern “B”
Figure 1B. 1991 SCAG Representative Activity Pattern “1”

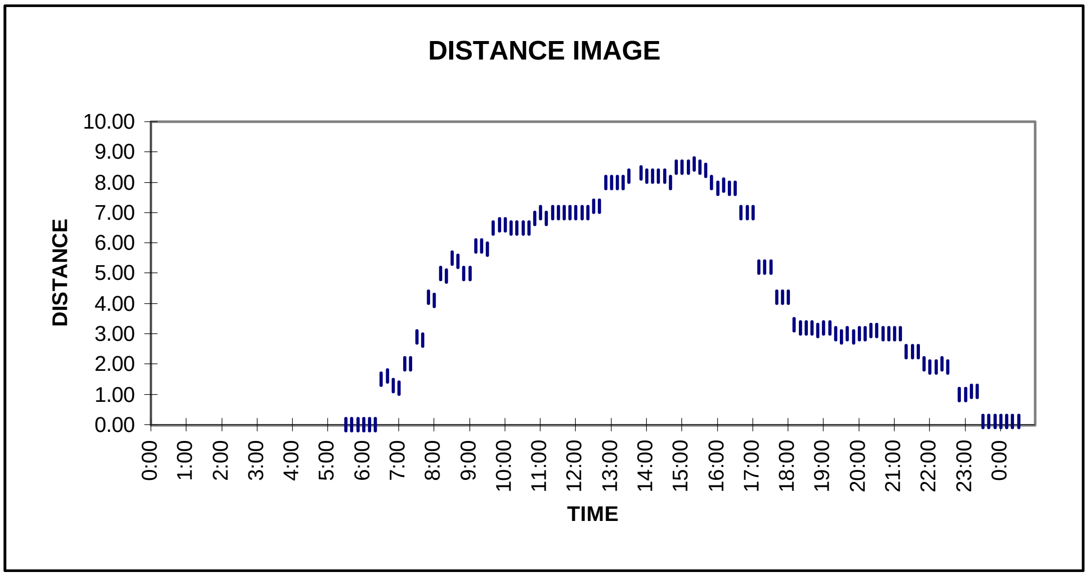
Figure 2A. 1976 SCAG Representative Activity Pattern “H”
Figure 2B. 1991 SCAG Representative Activity Pattern “2”

Figure 3A. 1976 SCAG Representative Activity Pattern “F”
Figure 3B. 1991 SCAG Representative Activity Pattern “3”

Figure 4. A GIS-based Microsimulation of Activity Patterns - Potential Destinations

Figure 5. A GIS-based Microsimulation of Activity Patterns - Destination Choice





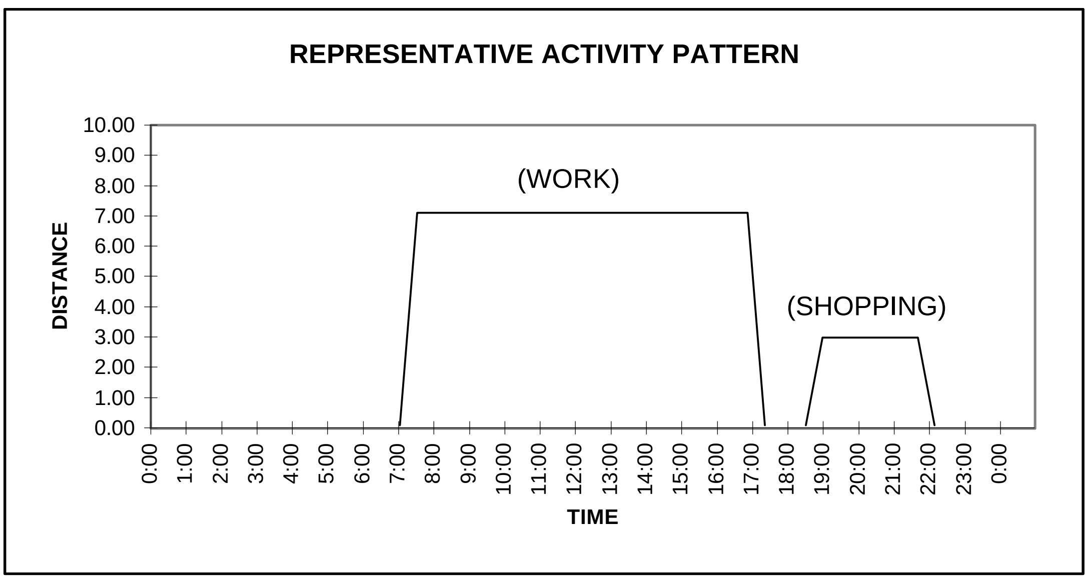
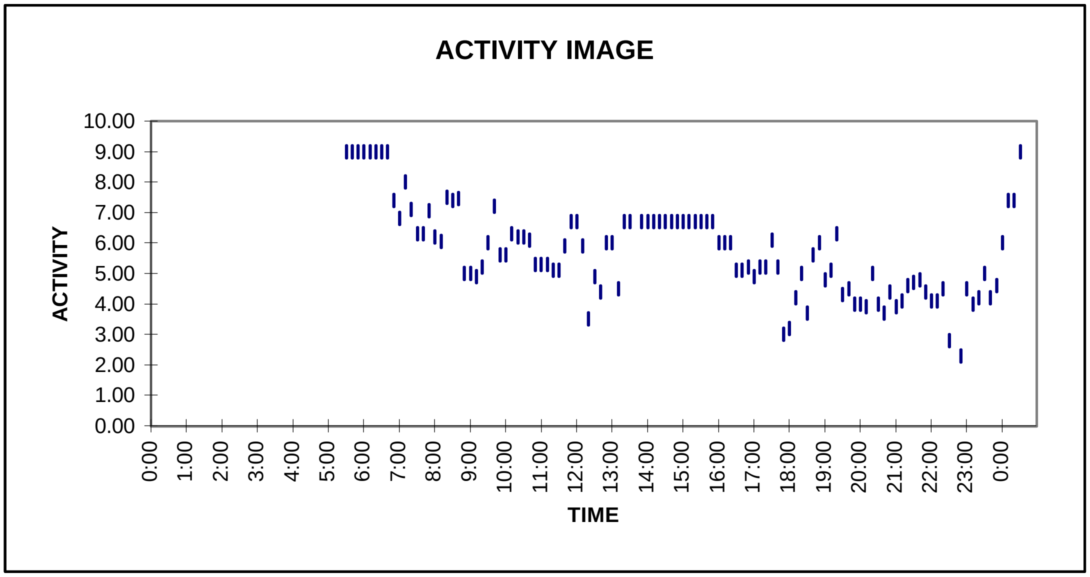
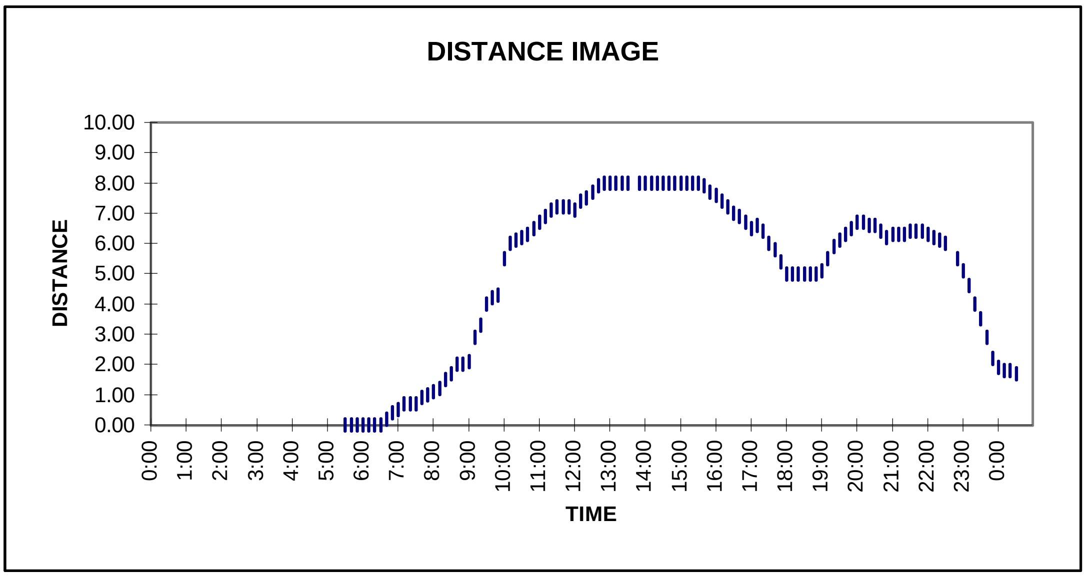


FIGURE 1A. 1976 SCAG Representative Activity Pattern "B"





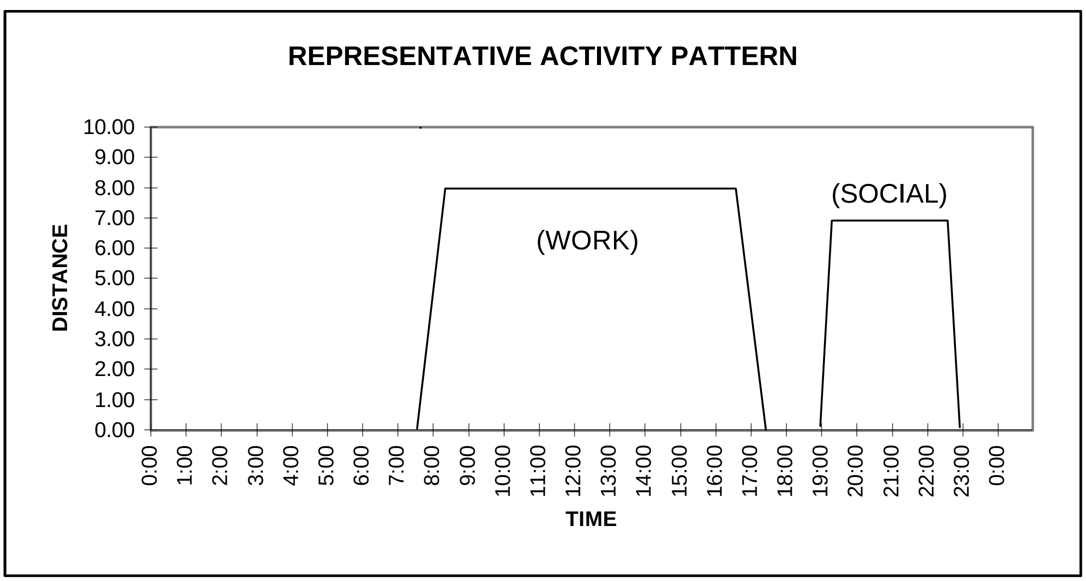
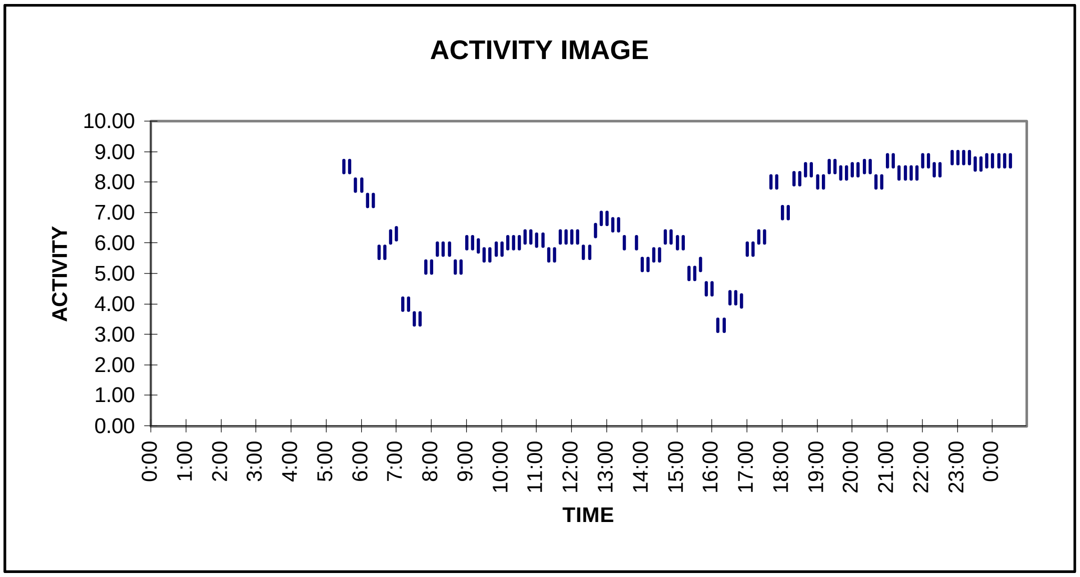
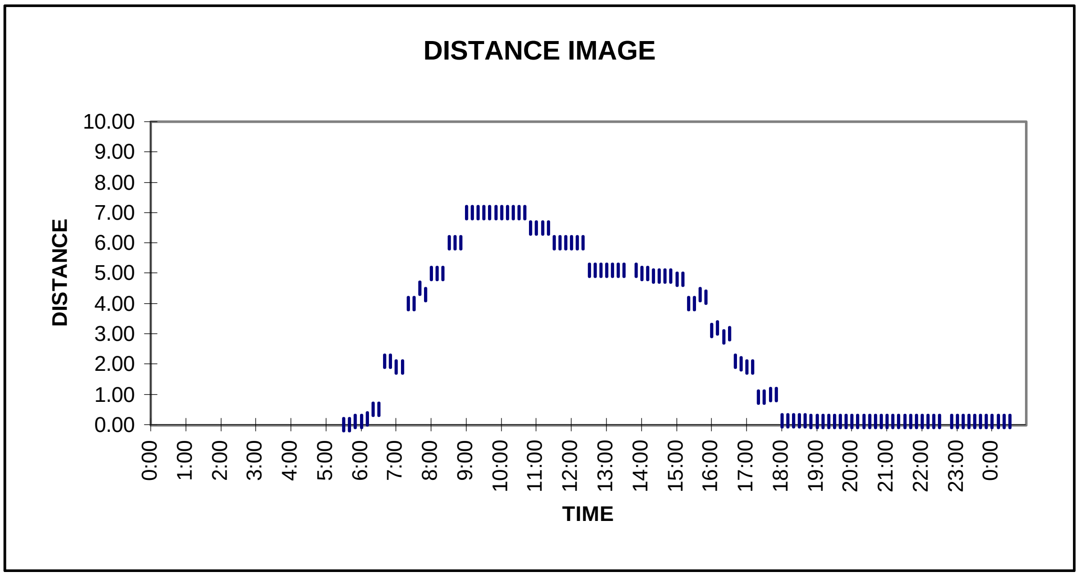


FIGURE 1B. 1991 SCAG Representative Activity Pattern "1"





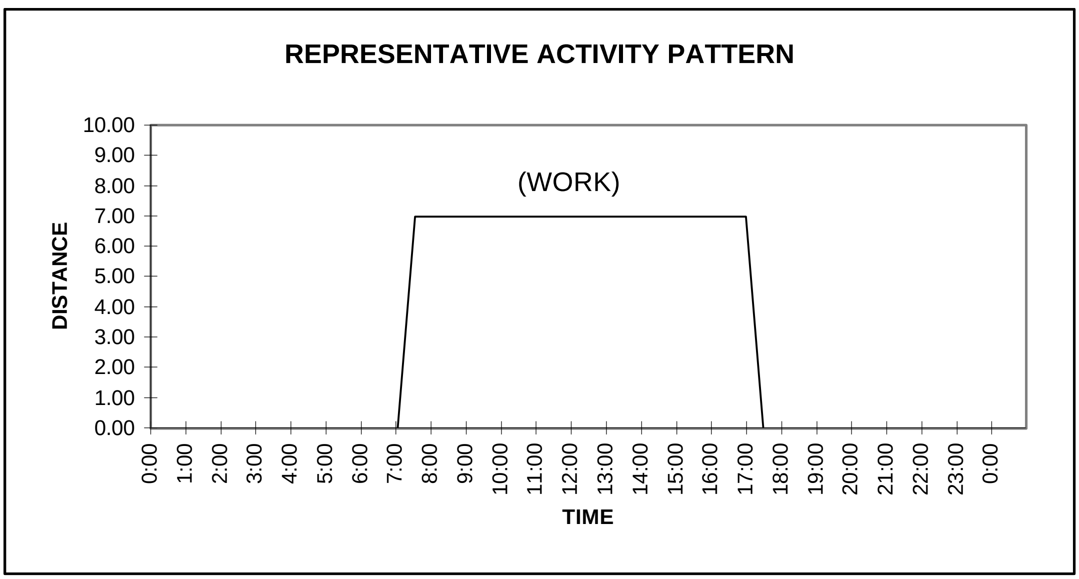
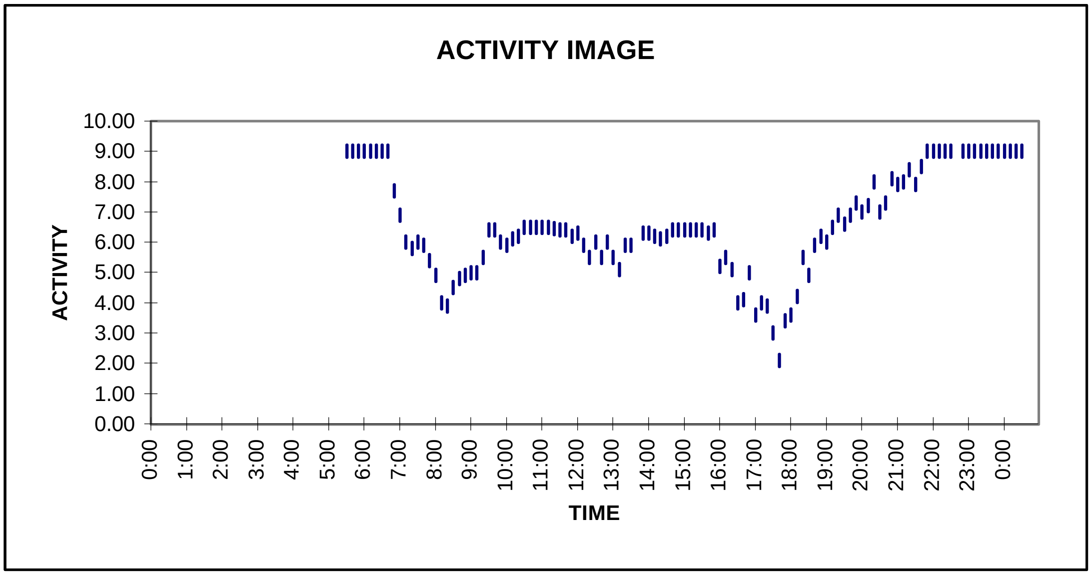
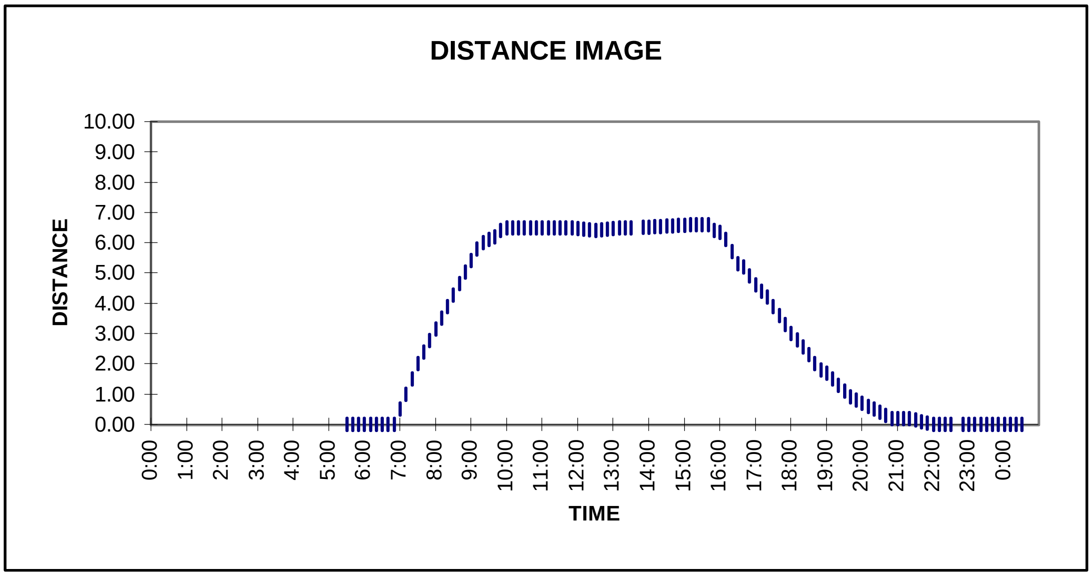


FIGURE 2A. 1976 SCAG Representative Activity Pattern "H"





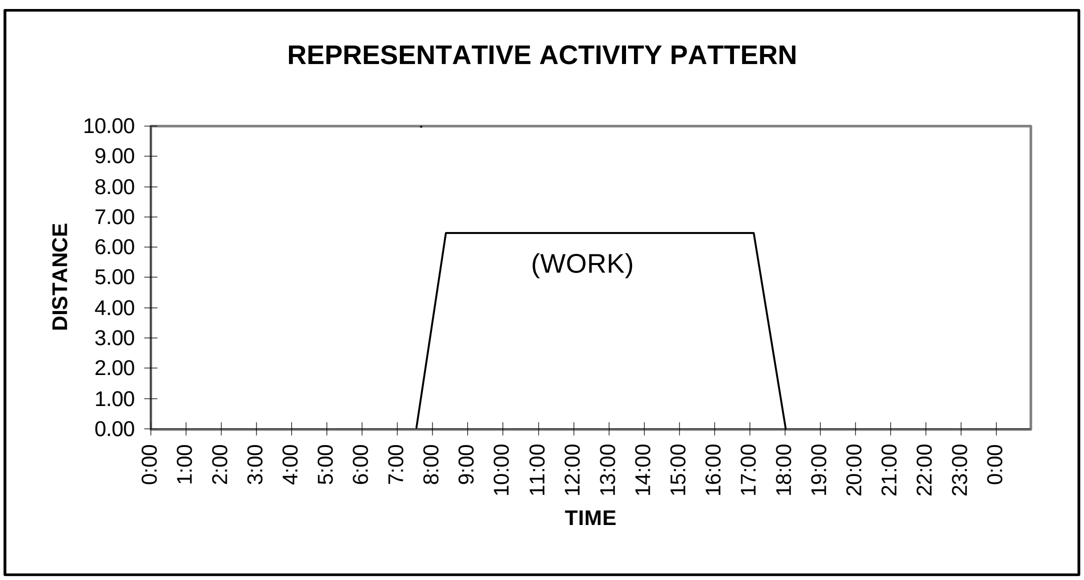


FIGURE 2B. 1991 SCAG Representative Activity Pattern "2"

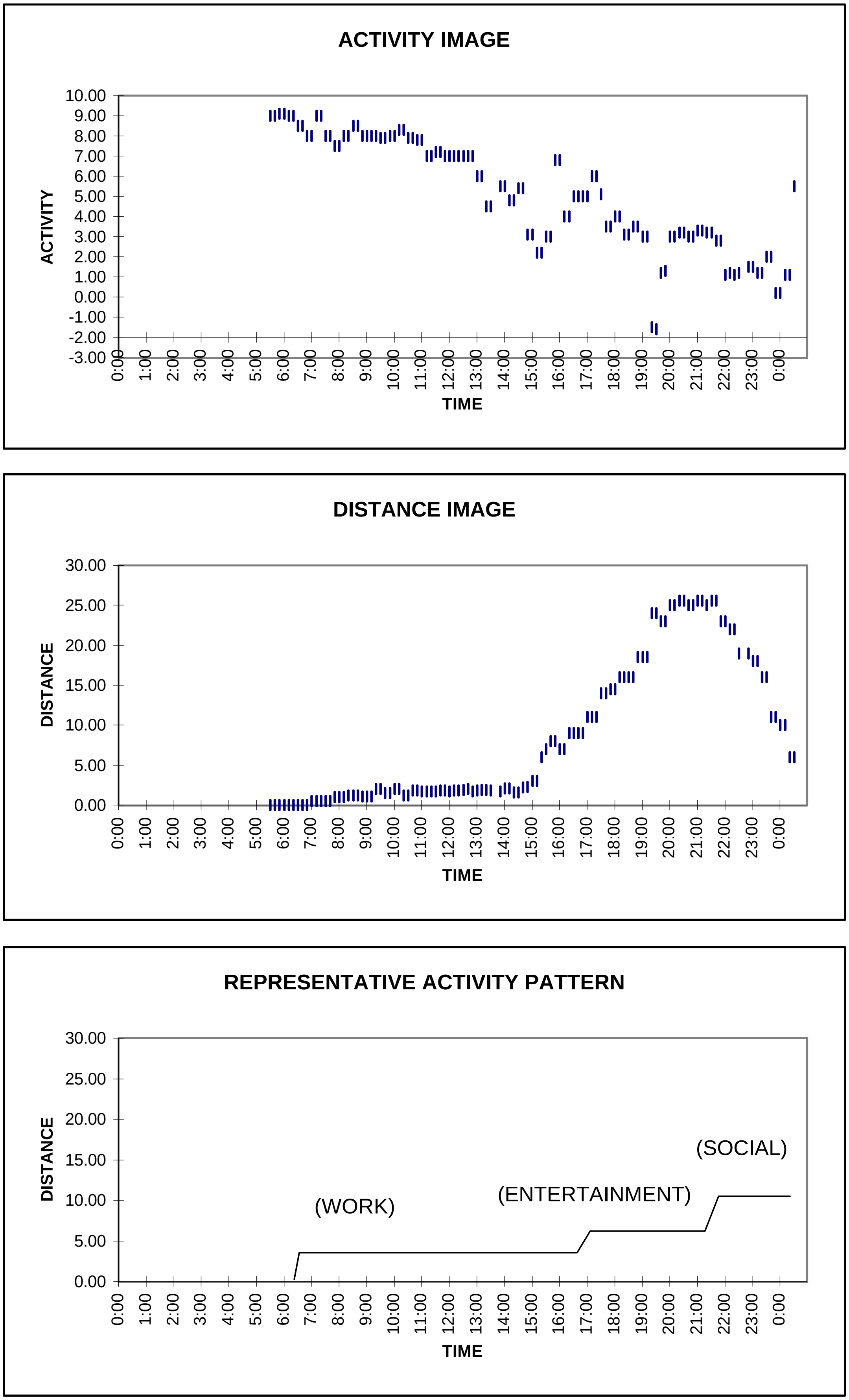
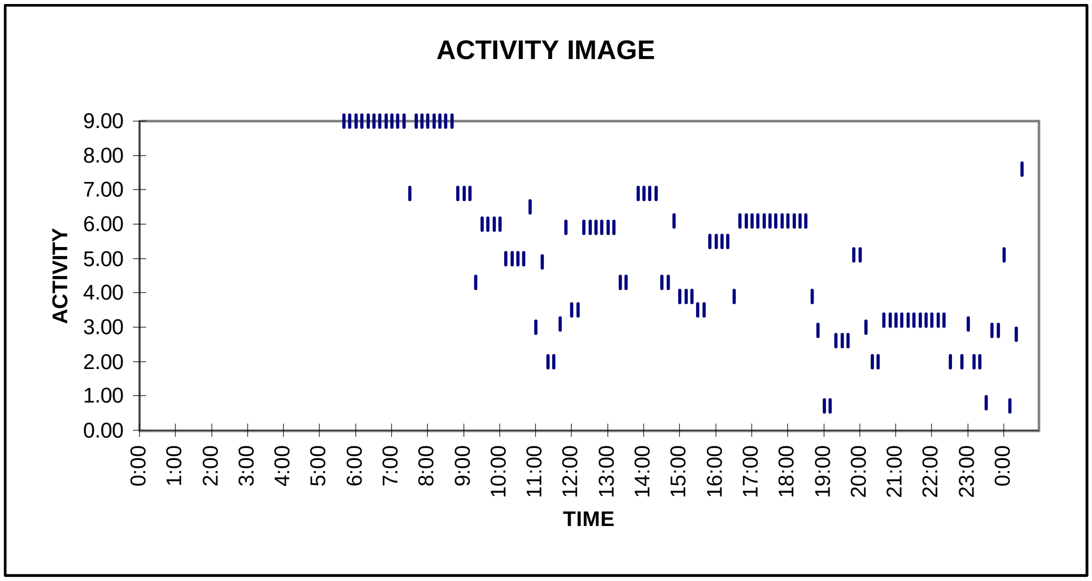
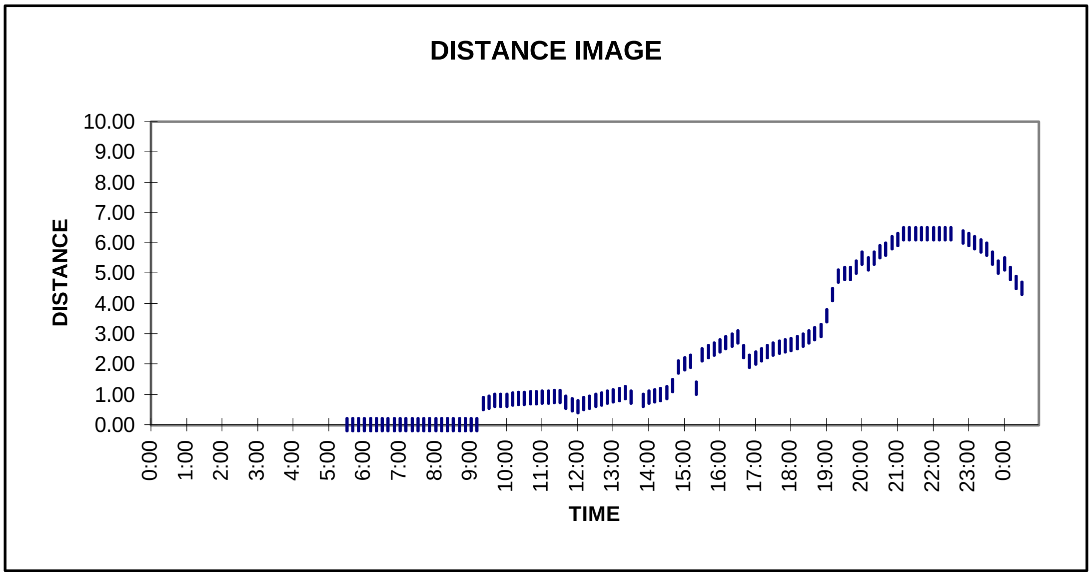


FIGURE 3A. 1976 SCAG Representative Activity Pattern "F"





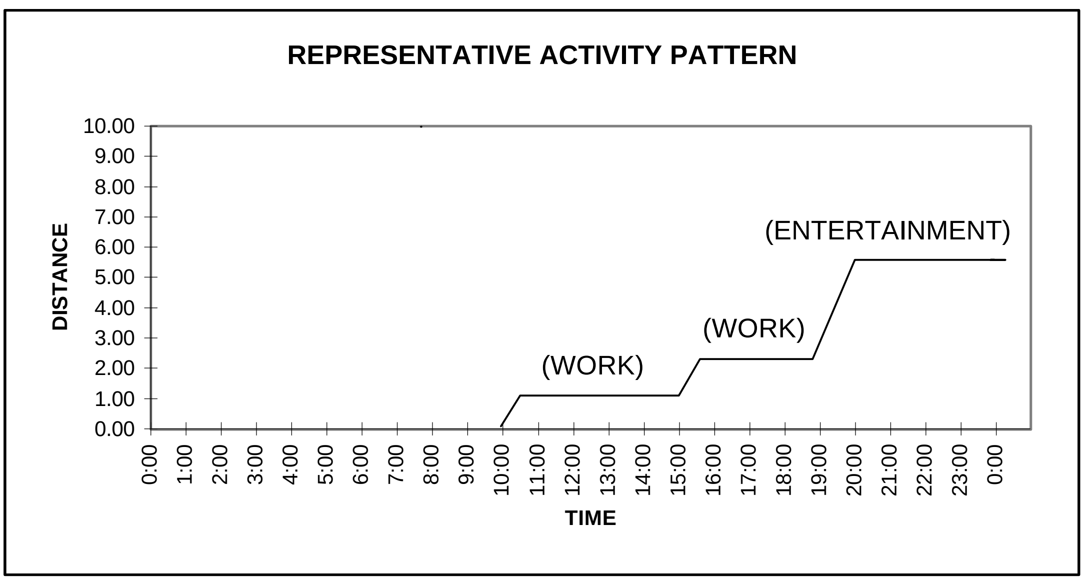


FIGURE 3B. 1991 SCAG Representative Activity Pattern "3"

Figure 4. A GIS-based Microsimulation of Activity Patterns - Potential Destinations

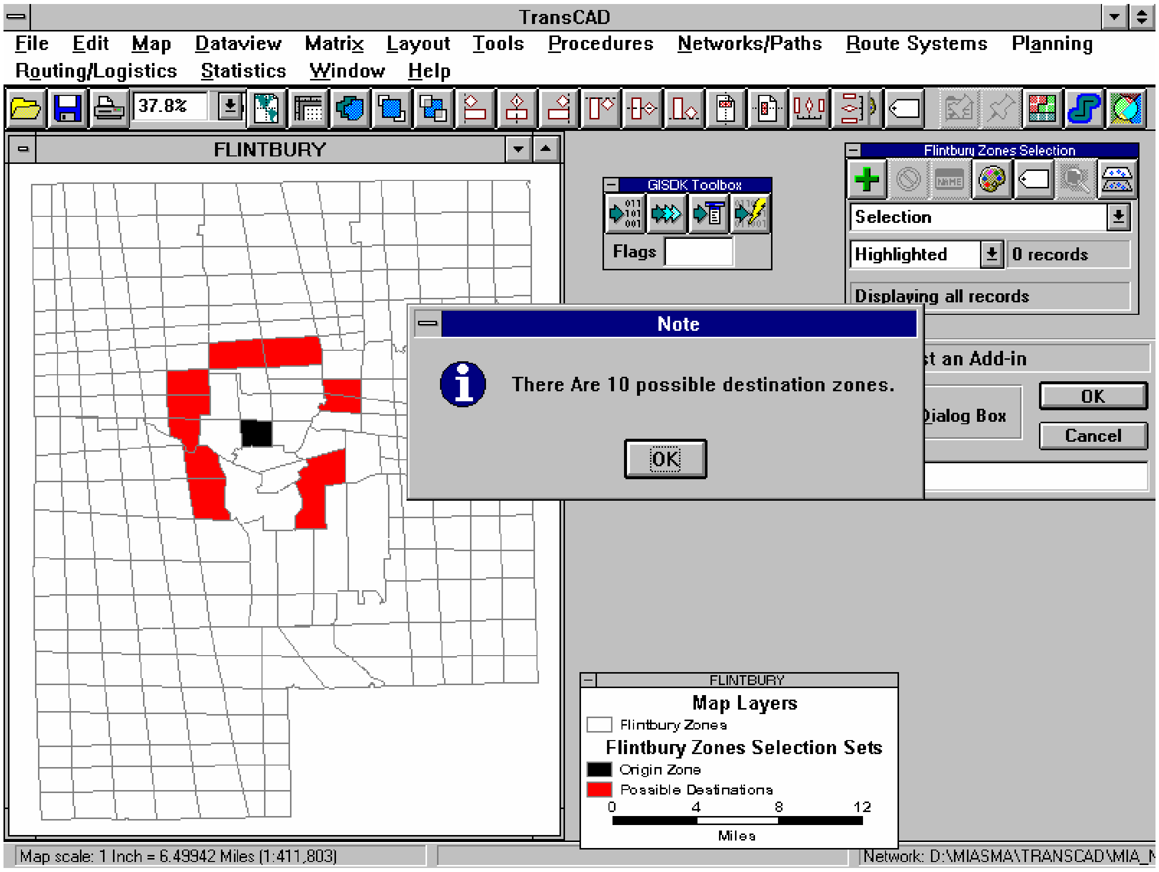


Figure 5. A GIS-based Microsimulation of Activity Patterns - Destination Choice