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# A Microsimulation of Daily Activity Patterns

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## **A Microsimulation of Daily Activity Patterns**

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by

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### **ABSTRACT**

This paper documents the prototype development, application, and validation of a pattern synthesis model based on activity-travel pattern classifications. The technique proposed is a microsimulation approach to construct daily activity patterns for individuals established on empirical distributions of representative activity patterns and distributions of additional travel characteristics contained by every pattern. The method clearly recognizes the complex, stochastic nature of activity-travel behavior in terms of activity generation, spatial choice, and scheduling components. A successful application of the model is outlined using data from the 1994 Portland Activity Travel Survey.

**KEYWORDS** activity-based approach, activity patterns, microsimulation

**WORD COUNT** 6100 and 6 figures

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## 1. INTRODUCTION

This paper describes the development of an activity-based microsimulation model for travel demand forecasting, and is part of a larger research effort aimed at the emergent transportation planning methodologies designed to address the limitations of current modeling practice in meeting current legislative and judicial mandates. The model builds upon existing research demonstrating that travel behavior should be viewed holistically using activity-travel patterns, a time-dependent representation of the activities and their attributes in which an individual engages. A microsimulation approach integrated with a geographic information system is advanced to synthesize individual, 24-hour activity-travel patterns for households that are reflective of the available transportation and land use system. By using activity-travel patterns as the basis of the simulation approach, the timing, sequencing, and connections between activities are explicitly included in a process where previously they would be disregarded. The final product of this research is a prototype modeling system that has the potential to replace some or all aspects of the traditional 'four-step' model.

The next section provides an overview of the simulation approach. **Section 3** presents a short discussion of the aggregate activity-travel pattern classification and results, while **Section 4** summarizes the implementation of the generation model. **Section 5** demonstrates a prototype application of the simulation approach. Finally, **Section 6** concludes this paper by summarizing the contribution to travel behavior analysis and suggests some extensions to the work.

## 2. FRAMEWORK FOR AN ACTIVITY-BASED GENERATION MODEL

The primary motivation of this paper is to document the development of the simulation approach for travel demand forecasting. While there is great enthusiasm towards a shift to activity-based microsimulation models in the travel demand community, more work is needed to develop models that can generate activity participation and travel demand for a population. The activity-based approach has emerged from the desire to model travel behavior by understanding the nature of activity participation that inspires it. It identifies travel as derived from the desire to participate in activities dispersed both in space and time, specified as daily or multi-day patterns of behavior (Hagerstrand, 1973). The following is a summary of the major characteristics of the activity-based approach (McNally, 1996):

- a) Travel demand is derived from activity participation
- b) Activity participation involves generation, spatial choice, and scheduling components
- c) Activity and travel behavior are delimited by temporal and spatial constraints
- d) Linkages exist between activities, locations, times, and individuals
- e) A number of decision paradigms are probable

An activity-based model, for the purposes of this paper, is defined as a model that attempts to describe any or all aspects of activity participation and includes necessary constraints and linkages. Minimally,

activity-based models must incorporate activity and scheduling and activity locations in a time-dependent fashion (i.e., activity-travel patterns or multiple tours).

A core difficulty in developing activity models is trying to capture such complex behavior in a single entity for use as the primary unit of analysis. With the 4-step, the “trip” was defined as the primary unit of analysis, facilitating initial model development but severely limiting realistic depiction of travel behavior. The equivalent in the activity-based approach could be activities, tours, or patterns; but no real consensus has emerged regarding the representation of the activity-travel pattern for a number of reasons.

For this research, the activity-travel pattern is defined using an extension of method developed by Recker et al. (1983): an individual level depiction of the activity type, distance from home, distance between last activity, mode used, or other variables of interest over a 24 hour time period sampled at 10 minute intervals. All out-of-home activity types are defined in the following manner: work (work, work-related, and school), maintenance (dine out, shopping, etc.), and discretionary (visiting friends, social party, etc.). Next, all in-home activities are characterized as home. This construct is used to (1) reduce the complexity of characterizing a large number of activities over the 24-hours and (2) these types of breakdowns have been shown to be useful with respect to individual activity behavior. Third, spatial dimensions can be included through two variables: “distance from home” and “distance from last activity”. Finally, other variables can be used including mode and accompanying family members for each activity. The activity travel pattern is minimally defined on just the activity dimension, and possibly additional spatial and other defined variables over a 24-hour time period at 10-minute intervals (144 time steps). The advantages of this type of representation are that it is very straightforward to implement, can describe a large number of attributes along the temporal dimension, and once assigned to an individual, can be aggregated into trip tables and used on standard transportation models (see McNally, 1999).

This paper first focuses on design issues related to the development of the modeling system and then considers the details of particular sub-models. The foundation for this model is an aggregate classification of individual activity-travel patterns that produces a number of representative activity patterns (RAPs) which are groups of similar individual activity-travel patterns. The classification provides a means of identifying the choice probability distributions associated with each RAP and the underlying activity type, location, and duration dimensions for each RAP. These probability distributions are derived from the observed activity-travel behavior of the individual observations that comprise each RAP. The distributions are then used to simulate entire activity-travel patterns—from the RAP-type to the time-dependent sequence of activities, durations, and locations—using a multi-stage Monte Carlo simulation (MCS) coupled with a geographic information system. MCS is a technique of randomly sampling from a specified probability distribution numerous times in a fashion that accurately represents the overall distribution. The distribution of the values determined for the model outcome reflects the probability that the values could occur.

Initially, a household is selected from the population. For each individual household member, the identified RAP choice probabilities are assigned based on the individual's socio-economic characteristics. The first stage of the MCS assigns a RAP to the individual in consideration based on the identified RAP likelihoods. The second stage simulates a 24-hour activity-travel pattern: minimally, a sequence of activities, each with a type, start time, duration, and location. The process generates an activity conditional on the distributions associated with the assigned RAP. Activities are generated in a temporally sensitive, sequential manner until an entire 24-hour period activity-travel pattern is constructed. Starting at time step one, the procedure simulates an activity type, its duration, and location from the observed activity distribution associated with the assigned pattern and time step. At the finish of that first activity, a new activity and its characteristics are selected based on the activity participation characteristics near the current time step. This process continues until the entire 24-hour pattern is specified for the individual under consideration. An advantage of such a structure is that it allows for both RAP and time-dependent nature of the activity participation and its characteristics (duration and location) to be modeled in a straightforward manner. One potential drawback of the model as designed is that the process could get "stuck" at a time step (unable to generate an acceptable location or duration), though this can be solved with structural means. Another drawback is that noise or outliers may skew the simulation. If these or other problems cause an individual's pattern to be ill specified in this manner, the pattern may be discarded and the entire pattern synthesis restarted for the individual. The activity-travel pattern output by this stage is only provisional because distances are assigned only as general parameters.

To allow the generated activity-travel pattern to reflect this activity distribution, the final stage of the MCS updates the general location parameters with specific activity locations using a GIS updating procedure. Given the household's location and starting from the beginning of each household member's activity-travel pattern, the activity locations reflecting the activity distribution available to the household and satisfying the constraints of the assigned pattern (e.g., distance from home and distance from the last activity) are identified within the GIS. The potential locations, either zones or x-y coordinates, are assigned a likelihood, most likely proportional to the density of nearby land use variables depending on the activity type. Once probabilities are assigned to all the locations a MCS is conducted and a location selected. All the activities in the synthesized pattern are assigned locations in this manner. If all activities in the individual's pattern can successfully be assigned locations, then the next individual's activity-travel pattern is simulated in the same fashion until the entire household has been simulated. If not, depending on the severity of the failure, either the locations are re-simulated or an entirely new activity-travel pattern is simulated for the individual.

At a minimum, the simulation approach can be reduced to an activity pattern generation model, which can replace conventional trip generation models by converting the assigned patterns to trips. More likely, the simulation approach could replace both the trip generation *and* distribution models by producing either static ( by aggregating time slices over some period of peak period of time) or dynamic (minute-by-minute)

origin-destination trip tables through the simulation of a fully specified activity-travel patterns with all activity-scheduling attributes, including activity locations that correspond to actual geographic locations. Static trip tables can then be input into the mode choice and route choice stages of conventional models, while the dynamic trip tables can serve as input to dynamic traffic assignment or traffic simulation models (TRANSIMS, Paramics, etc.) with the aim of replacing outright the conventional forecasting process. Either approach would eliminate a number of shortcomings of current approaches.

Similar to Vaughn et al. (1997) and McNally (1999), the simulation approach does not make any assumptions regarding the process by which individuals schedule or execute activities. Rather, it aims to replicate the observed behavior of individuals. Further, the simulation approach's adoption of MCS with RAPs offers many modeling benefits. First, the distributions of the activity-travel patterns can be empirically derived. Second, correlations and pattern interdependencies can be modeled. For instance, activity durations that are correlated with the activity type can be incorporated into the simulation. Third, the data requirements of the structural model are parsimonious and easily constructed. Fourth, greater levels of precision can be achieved by increasing the number of iterations. Fifth, the model's behavior can be fairly easily. Sixth, it applies valid and widely recognized techniques. Finally, model performance can be directly compared with current forecasting models.

This overview of the simulation approach will be expanded with a discussion of the specific nature of the sub models later in the paper. In addition, an illustration of the simulation approach will be provided using a subset of the 1994 Portland Activity Travel Survey. The approach presented addresses this need using an inherently activity-based framework that incorporates spatial and temporal dimensions alongside lifestyle effects. It is hoped that this model system can eventually improve if not replace the trip generation and distribution stages of the current travel demand modeling process.

### **3. AGGREGATE CLASSIFICATION OF ACTIVITY-TRAVEL PATTERNS**

The simulation approach uses as its foundation the activity-travel pattern and RAP generation as described in the previous section. Classification is involved in the categorization of individual activity-travel patterns into a limited number of RAPs. Underlying the use of classification of activity-travel patterns is the belief that there exist groups of individuals with similar travel behavior that can be captured in the RAPs. By distinguishing these patterns, it is possible to deal with the complete daily activity-travel patterns of individuals in a holistic manner. Both Recker et al. (1983) and Pas (1983) have shown that much of the daily variation in activity-travel patterns can be captured through classification into a few pattern types and that "the choice of daily pattern type was closely related to socioeconomic characteristics describing household role, lifestyle, and lifecycle" (Vaughn et al. 1997). Recent work presented in McNally (1999) and Wang (1996) has bolstered the prospects for using RAPs as the basis of forecasting models by showing preliminary evidence that RAPs are stable over conventional planning horizons (10 years).

Still, while a strong body of research has been built around RAPs, a key methodological question remains concerning application of the approach. Specifically, it is unclear as to how the relationship between RAPs and socioeconomic characteristics should be constructed: should socioeconomic characteristics be related to RAPs or should RAPs be related to socioeconomic characteristics? Wang (1996) opted for the former by first specifying six lifecycle groups and clustering the groups independently to identify RAPs. The problem with this method is that some of the identified RAPs in the different lifecycle groups are redundant and a full scale clustering must be more efficient. The advantage to this is that the patterns are more homogeneous when split first allowing for differences to be identified that may not originally be found. The other approach is to distinguish RAPs first and subsequently link them to socio-economic characteristics. While efficient, many of the subtle differences between activity-travel patterns will be lost in the RAPs. Consequently, accuracy of any model developed on the results may suffer.

The activity-travel pattern classification used by the simulation approach is developed using a hybrid of the two approaches described above. First, individuals are segmented into three broad lifestyle groups based on employment status and age: children, full-time employed adults, and adults not employed full-time. These categories are selected because previous research indicates that the age and employment status captures a significant portion of the variance in activity-travel behavior (Vaughn et al., 1997). Next, the individual activity travel patterns of each segment are classified to identify a number of distinct RAPs specific to each of the three defined categories. The advantage of this construction is that the homogeneous RAPs are identified in a non-redundant manner. For instance, those adults that are employed full-time are likely to have similar patterns regardless of their socioeconomic attributes. A possible drawback to this and similar classification methods is the question of focus: how detailed of a classification should be undertaken? With respect to the simulation approach, identifying more RAPs would likely lead to greater accuracy in the synthesis of patterns. However, at some point, care must be taken to prevent adding too many RAPs that may result in the capture of more noise than differences in travel behavior. It is at this point where the classification shifts from “science” to “art” and the difficulty of finding good clusters becomes apparent. Finally, for each of the age and employment status segments for which there are RAPs identified, additional dimensions can be applied, such as household lifecycle, number of cars, or additional commonly used variables in trip generation models. This allows the RAP assignment model to be sensitive to socioeconomic changes in a target population.

Note that for each category defined by age and employment status, a separate set of RAPs are defined. The advantage of the approach is that the classifications of activity-travel patterns are reduced without a substantial loss of detail in the defined RAPs. Once estimated, the application of the generation model to estimate patterns is straightforward. An individual’s placement in a category is deterministic as are the probabilities of participating in one of the identified RAPs for that category. A RAP is assigned stochastically using standard simulation techniques such as MCS.



### 3.1 Selection of Classification Data

The individual activity-travel patterns from the first of two travel days from the 1994 Portland Activity-travel survey are used to identify RAPs via a classification. The survey contains 10,008 individuals with 4,453 households. Only individual patterns that meet the following criteria are included in the classification: (1) complete data (location and times); (2) surveyed on a weekday; and (3) at least one out-of-home activity. In addition, only adults were considered in this prototype application to limit the complexity of the analysis. As a result, a total of 3,391 adults were included in the analysis. The original data was coded with 50 activity types that were then distilled into the four types described earlier: home, work, maintenance, and discretionary with travel treated implicit to any out-of-home and return home activity. The latter point is important especially in the classification because it treats the travel time to an out-of-home or return home activity as part of the activity itself. Further, those individual patterns meeting the criteria were split into two sets based on the characteristics of the individual as full-time employed adults (17 years of age or older) and non full-time employed adults (homemakers, part-time employment, retired, etc.). The actual split consisted of 1875 and 1516 adults, respectively.

### 3.2 Classification Methodology

The classification is similar to the standard k-means methodology applied previously by Recker et al. (1983). Modifications from the original approach were made in (1) the final individual pattern attributes included and (2) calculating the distance between an activity-travel pattern and a RAP as part of the k-means clustering algorithm. Addressing the first point, a number of classifications were conducted with a combination of the variables activity type, distance to home (miles), and the distance between last activity (miles) defined for each time step with the “best” result being selected for further analysis based on quantitative and qualitative factors. Note that the distance measures are Euclidean distances and not network distances, though the model can easily incorporate network distances. To calculate dissimilarity as part of the clustering algorithm, each of the three attributes is treated as a nominal variable allowing the classification to include a variety of data types. When comparing two patterns, for each time step the three attributes (activity type, miles from home, and miles from last activity) are compared. For each attribute that is “different”, the dissimilarity measure is incremented (otherwise, the dissimilarity measure is not affected). The activity type attribute is nominal by definition. However, the distance from home and distance from last activity attributes must be converted into nominal variables in the similarity calculation. This is done at each timestep by considering the attribute as the same as the RAP centroid it is being compared to if it comes within a threshold of 20 percent of the RAP centroid’s value. Therefore, the similarity of a particular RAP and an activity-travel pattern will range from 0 to 432 (144 time steps \* 3 variables), corresponding from being exactly alike to very different if all three attributes are selected to define the activity-travel patterns. The advantage of this method is that it treats the activity and the distance attributes (miles from home and miles from last activity) with the same binary metric.

Once the initial classification results are compiled, sets of rules were developed for each subset to clarify the specific definition of the RAPs and reduce the variability of the activity composition of the pattern members. The rules are expected to be useful in both developing an aggregate sense of what the RAPs represent in terms of activity behavior (that is, market segments) and for quickly classifying and comparing new, observed activity-travel patterns to those developed (and to eliminate the use of clustering-type algorithms in extensions to this work). The rules constructed are mutually exclusive, collectively exhaustive, and are applied in a hierarchical fashion through a collection of if-then-else statements that assign patterns to only one RAP. They are developed after an empirical analysis of the cluster results for each of the previously examined subsets. The individual patterns are then reassigned to the RAPs based on the developed rules and all subsequent analysis and models use the “rule-based” RAPs.

### 3.3 Classification Results

Initially, all three attributes (activity type, distance from home and distance between last activity) were used in the classification process. However, after the initial results, it became clear that using just activity-type as the only variable making up the activity-travel patterns would be sufficient to identify the RAPs *in the classification process*. In effect, the same patterns were being duplicated in the clustering with only slight distance differences. As a result, all subsequent clustering used only activity-type defined over each time step to model each activity travel pattern.

#### Adults Employed Full-time:

The classification for adults employed full-time produced the following five RAPs, each with a short description of the main activity profile of the pattern:

- a) Standard Work - A single 8 hour work activity between 8am and 5pm
- b) Power Work - A single 10+ hour work activity between about 8am and late
- c) Late Work - An 8 hour workday starting in the afternoon
- d) Work-Maintenance (Multiple Work) – Multiple Work activities, usually with a lunchtime out-of-office maintenance activity
- e) Various Short Activities – Multiple activities for short times nearby home

Note that employed adults do not necessarily have a work activity on the generated pattern.

#### Adults Not Employed Full-time:

The classification for adults not employed full-time produced the following four RAPs:

- a) Work/School - An 6 hour workday or school day between 8am and 5pm
- b) Maintenance - Several mid-day maintenance activities lasting a few hours
- c) Discretionary - Several mid-day discretionary activities lasting a few hours
- d) Various Short Activities - Mostly stayed home; some short, nearby activities

A more detailed analysis, including an overview of the socio-economic makeup of the identified RAPs, the activity profile of each RAP, and the classification rules developed from the RAPs is provided in Kulkarni and McNally (2000).

#### 4. SIMULATION METHODOLOGY

The aggregate classification of individual activity-travel patterns into RAPs provides the seeds for synthesizing activity-travel patterns, providing essentially an instrument for estimating the choice probability distributions of each RAP and associated activity type, location, and duration dimensions. The general outline for the pattern synthesis was described in **Section 2**; here, the required distributions needed to simulate synthetic patterns and the details of their construction are documented. An example is developed for the Standard Work RAP of Adults Employed Full-time, herein referred to as Standard Work RAP. **Figure 1** shows the activity profile for the Standard Work RAP. The activity profile identifies the proportion of the RAP members that are participating in each specified activity type (home, work, maintenance, and discretionary) at each time step for the Standard Work RAP and generally provides a good snapshot of the RAP from which the RAP description can be visualized.

The simulation approach requires that a target RAP first be specified for a selected individual. The probability that an individual will engage in each identified RAPs are empirically estimated from the classification results. If the individual whose pattern is being synthesized were over 17 and employed full-time, the likelihood that he would engage in any of the six identified RAPs is shown in **Table 1**; the target RAP can be randomly assigned. Alternately, extending **Table 1** to produce trip productions that could be used as input into conventional trip generation models could serve as a bridge between current trip-based and emerging activity-based modeling approaches. Such an application would have an immediate impact in improving conventional trip generation models by addressing time-of-day and trip purposes in a more direct manner.

**TABLE 1 RAP Assignment Model for Adults**

Employment Status	RAP Name	Frequency	Proportion
Full-time	Standard Work	623	33%
Full-time	Power Work	156	8%
Full-time	Late Work	67	4%
Full-time	Work-Maintenance	744	40%
Full-time	Various Short Activities	285	15%
Not Full-time	Work/School	472	31%
Not Full-time	Maintenance	386	26%
Not Full-time	Discretionary	295	20%
Not Full-time	Various Short Activities	363	24%

For the simulation approach to produce fully specified activity-travel patterns, activities and the associated durations and locations, have to be sampled from the distributions associated with the target RAP. The probability that an individual engages in a Home, Work, Maintenance, or Discretionary activity is derived empirically by the percentage of the specific activity starts *at each time step* (within 30 minutes) for all the individuals that define the RAP. **Figure 2** provides a detailed profile of the mean proportion of activity starts by time step developed for the Standard Work RAP of Adults Employed Full-time. For instance, 94 percent of all activities that start within a half-hour of 7:00 are Work activities, while the remaining 6 percent are Maintenance activities. Note that Travel activities are excluded from the activity engagement probability and are implicitly included as part of the Work, Maintenance, Discretionary or Return Home activity. That is, the activity stop duration is assumed to include travel time.

For the duration, the average (and standard deviation) duration for each Home, Work, Maintenance, and Discretionary activity that starts 30 minutes within each time step (where the time steps are defined at ten minute intervals providing a one hour time window) is estimated for each RAP. **Figure 3** provides a detailed profile of the mean activity durations by starting time step and activity type developed for the Standard Work RAP of Adults Employed Full-time. To assign duration to an assigned activity at a particular time step, the mean duration (and its standard deviation) can be used as sampled from **Figure 3** using a modified normal distribution.

Next, the general location is assigned to the activity, defined as the Euclidean distance from home to the Work, Maintenance, or Discretionary activity (alternately referred to as distance). The average (and standard deviation) distance from home for each Work, Maintenance, and Discretionary activity that starts

30 minutes within each time step is estimated for each RAP. **Figure 4** provides a detailed profile of the mean activity distances by starting time step and activity type developed for the Standard Work RAP of Adults Employed Full-time. To assign the distance from home to an assigned activity at a particular time step, the mean duration (and its standard deviation) can be used as sampled from **Figure 4** using a modified normal distribution. Once an activity type, duration, and location are ascribed using the constructed distributions, a new activity type, duration, and location are randomly selected at the time step when the previous activity is completed. This continues until the entire 24-hour activity-travel pattern is completed.

The simulation approach is developed using a client/server framework where the client is a Visual Basic application. It provides the user interface and controlling structure to synthesize activity-travel patterns with activity type, sequencing, duration, and conditional distance measures. A database server is developed that can be queried to provide the RAP parameters and distributions to be sampled. The purpose of the RAP database server is to link the simulation to the identified RAP distributions. The database is created in MS Access and contains several linked tables that can be queried using SQL. The following tables and a short description of their contents are provided:

- a) Group RAP Table - The likelihood of engaging in an identified RAP defined by the age and employment status of the individual.
- b) Activity Start Table - The likelihood that given a RAP and time step, that an individual will start a Home, Work, Maintenance, or Discretionary activity.
- c) Activity Duration Table - The likelihood that given a RAP, a time step, and an activity (Home, Work, Maintenance, or Discretionary) at the time step, the mean duration and its standard deviation.
- d) Activity Distance Table - The likelihood that given a RAP, a time step, and an activity (Home, Work, Maintenance, or Discretionary) at the time step, the mean distance and its standard deviation.

Finally, a geographic information system server is developed that updates the conditional distance measures with actual x-y locations representative of the land use-transportation system available to an individual. This component of the simulation approach is built from a set of ESRI MapObject components, providing a flexible approach for displaying, modifying, and manipulating network and land use coverages.

## 5. PROTOTYPE APPLICATION

A limited application of the simulation approach was conducted to test the aggregate accuracy of synthesized activity-travel patterns. Transportation network, land use, and employment data for the area has been obtained from Portland Metro sources (ArcView "shape files") and supplemented by data available from the Metro's 1994 Portland Activity-Travel Survey. The simulation approach was applied to synthesize 100 24-hour individual activity-travel patterns that consisted of activity type, start time, duration, and distance from home for the Standard Work RAPs from the socio-economic group Adults Employed Full-time.

Several statistics were calculated with the intention of validating the results. First, the activity profile (activity participation by time step) of the original Standard Work RAP activity profile (**Figure 1**) is compared to aggregated activity profile of the 100 synthesized patterns (**Figure 5**). For each activity type, the mean error (ME), mean absolute error (MAE), and root mean square error (RMSE) were calculated based on the difference between the mean forecasted activity participation from the 100 synthetic patterns and the actual activity participation from the identified Standard Work RAP's pattern (**Table 2**). Activity participation by type – Home, Work, Maintenance, and Discretionary – were included separately for each of the mentioned parameters. Generally, ME gives an idea if the simulated patterns have a bias towards particular activity types. It is not bounded on either side to zero. MAE and RMSE provide insight into accuracy of the synthetic patterns, with both bounded at the low end by zero and RMSE more sensitive to larger error. Note that MAE averages the absolute value of the error between the forecasted and observed activity percentage over all time steps while RMSE averages and takes the square root of the square of the error. Also calculated is the percentage of time steps that the synthetic patterns are different from the observed for the ranges indicated in **Table 3**.

The ME indicates that the forecasted patterns are slightly biased toward out-of-home Work, Maintenance, and Discretionary activities over Home activities. The MAE and RMSE parameters indicate that, in aggregate, the synthetic patterns are similar to the actual Standard Work RAP from which they were produced. On average over all time steps, the maximum error (Home activity) was less than 6%. Moreover, a large majority of the activities forecasted for each time step are within 5% of the Standard Work RAP (**Table 3**), with the largest category being “less than 1%” within the specified activity participation range. On a more disaggregate level, **Table 4** shows the synthesized activity chains versus the observed activity chains for the Standard Work RAP. Note that “Maint/Disc” indicates either a maintenance or discretionary activity and that sequentially repeating activities are indicated with the activity type followed by a “\*”. Results show that the on a disaggregate level, the simulation approach performs well. Further, more elementary activity chains are synthesized with greater accuracy more while complex patterns are more difficult to estimate.

**TABLE 2 Calculated Error Measures of Synthesized Standard Work RAP Compared to the Observed Standard Work RAP**

	ME	MAE	RMSE
Activity			
Home	-1.52	3.69	5.95
Work	0.98	3.15	4.99
Maintenance	0.46	1.39	2.11
Discretionary	0.08	1.09	1.70

**TABLE 3 Percentage of Time Steps Where Synthetic Standard Work RAP Activity Participation is Within Specified Range of the Observed Standard Work RAP**

	Home	Work	Maint.	Disc.
Range				
< 1%	44	44	55	71
1% - 2%	16	19	16	13
2% - 3%	7	3	15	8
3% - 4%	4	4	4	2
4% - 5%	1	4	3	2
> 5%	29	24	7	4

**TABLE 4 Synthetic Versus Observed Activity Chains for Standard Work RAP**

Type	Estimated	Observed
Home*--Work*--Home*	50%	50%
Home*--Maint/Disc*--Work*--Home*	7%	3%
Home*--Work*--Maint/Disc*--Home*	25%	14%
Home*--Work*--Maint/Disc*--Work*--Home*	0%	0%
OTHER --Single Tour	5%	8%
OTHER--Multiple Tours	13%	24%

The next step in the simulation is to add the spatial dimension to the simulation, adding both home locations and actual activity locations. **Figure 6** is a screenshot of the simulation approach demonstrating the current progress of work being done to incorporate this all-important dimension. The GIS-enabled version the simulation approach is applied to 100 synthesized Adults Employed Full-time randomly assigned home locations in the city of Beaverton (a suburb of Portland) and *all five identified RAPs for*

*Adults Employed Full-time were simulated in the test.* Locations for all activities were successfully assigned all 100 individuals. Exact x-y locations were assigned to each pattern by first selecting a random number of locations that satisfied the general distance parameters (in this case limited *only* to distance from home) and then assigning each a likelihood, proportional to the density of nearby employment depending on the activity type. In this instance, maintenance activities were assigned probabilities based on the retail employment while work activities use total employment. Once probabilities are assigned to all the potential locations, a MCS is conducted and location selected. The screenshot shows the home locations of the individuals as well as the selected x-y locations of all the activities in which the 100 (aggregated) individuals participated. While the greater spatial spread of work (W) activities is clear in the figure, the general locations of maintenance (M) and discretionary (D) activities is coincident with the location of households (H).

Overall, if the remaining RAPs have results that are similar to Standard Work RAP, the data indicates that the simulation framework successfully synthesizes the activity-travel patterns specified by RAPs and the distributions inherent within the RAPs. It is concluded that this was a successful application and test of the concept behind the simulation approach.

## 6. CONCLUSION AND FUTURE RESEARCH

The simulation approach is both unique and important in that it explicitly builds on a number of seminal concepts in activity-based research to develop a modeling framework. The advantage of using the simulation approach framework is that, by using RAPs, the conditional dependencies between the activity type, length, location, and starting time are explicitly captured with little cost. The key component of this effort is the development of daily activity-travel patterns that (1) replicate the overall distribution of the representative activity-travel patterns; (2) replicate the distributions of the characteristics within each of the representative activity-travel patterns; (3) adhere to the requisite spatial and temporal constraints; and (4) provide the necessary detail required of travel demand models by current planning legislation. An added advantage of this approach is that the generated individual activity-travel patterns can be converted into trip tables that can be used both in traditional assignment models and newer dynamic assignment techniques that require time-dependent trip tables. As a result, the model has the potential to replace some or all components of current travel demand models. Moreover, both the methodological and data requirements needed to apply the simulation approach are fairly simple allowing for ready adoption by practitioners.

The primary focus of the future research should be to better validate all the RAPs defined for adults to ensure the accuracy of the simulation approach's foundation. This includes expanding both aggregate (Chi-square tests) and disaggregate measures (better chaining measures). The secondary focus is to broaden the application of the simulation approach to include all individuals, including adults not employed full-time and children. This will allow for the system to be applied on a larger scale to generate origin-destination tables that can be tested against those generated by conventional models.



Several limitations exist in attempting to generate origin-destination trip tables using the simulation approach. First, intra-household constraints relating to the timing of activities, availability of household vehicles, joint activity participation, and others are not fully considered. Rather, activity-travel patterns initially are synthesized for each individual independent of other household members with out the necessary recombination. Possible solutions to this problem include setting up rules to integrate the individual patterns into a household or vehicle level pattern or adding a variable to indicate joint activity participation.

Second, the travel activity needs to have an associated mode. This would allow the correct number of trips to be simulated rather than activity. Both these issues are difficult, but critical to the accuracy of the simulation approach's forecasts and are currently being addressed.

On a broader note, this approach would have to predict activity pattern sensitivity to network changes in order for it be useful for short-term forecasting. In order for the model presented to do this, two changes would need to be made. First, actual network speeds (versus Euclidean distances or simple network distances) would have to replace the distance dimension. In addition, an iterative or dynamic framework equilibrating the activity locations with the actual travel times would need to be introduced. Second, a "memory " component needs to be introduced to predict the choice of activity by time of day. While there are a number of methods one could use to introduce memory, the method favored for further research and implementation includes replacing the current activity starts from a simple four choice set (home, work, maintenance, and discretionary) to a more detailed sixteen choice set that incorporates the likelihood that an individual from a RAP makes a *transition* from one activity to another activity at each time step along the lines of a Markov process.

Clearly, using only two socioeconomic groupings is liable to miss a lot of future shifts in travel patterns, particularly when prediction associated with socioeconomic change will likely affect RAP distributions within those groups. However, the model is not arbitrarily limited to two socioeconomic groupings as presented here. Rather, age and employment status make up the basis for identifying RAPs, which can be then related to additional socioeconomic groupings as desired by the modeler. An example of this is provided in the two activity-based pattern generation models presented in Kulkarni and McNally (2000) where automobile ownership and lifecycle group were incorporated into the model. By having the ability to include household structure, cars, and person attributes in addition to age, employment status, and generalized travel cost, the model can provide meaningful information for transportation system planning and policy analysis.

## 7. ACKNOWLEDGMENTS

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FIGURE 1 Activity Profile for Standard Work 623 Individuals

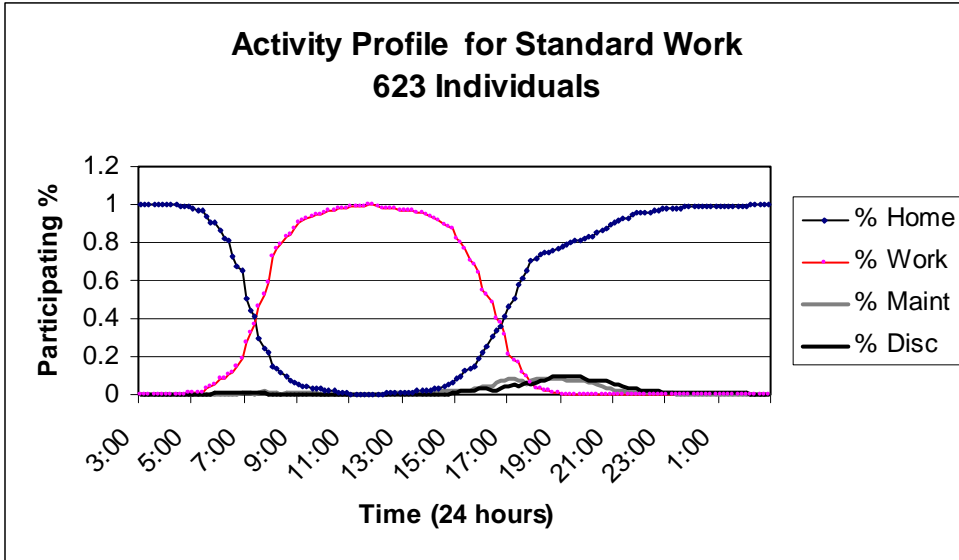


FIGURE 2 Activity Starts for Standard Work 623 Individuals

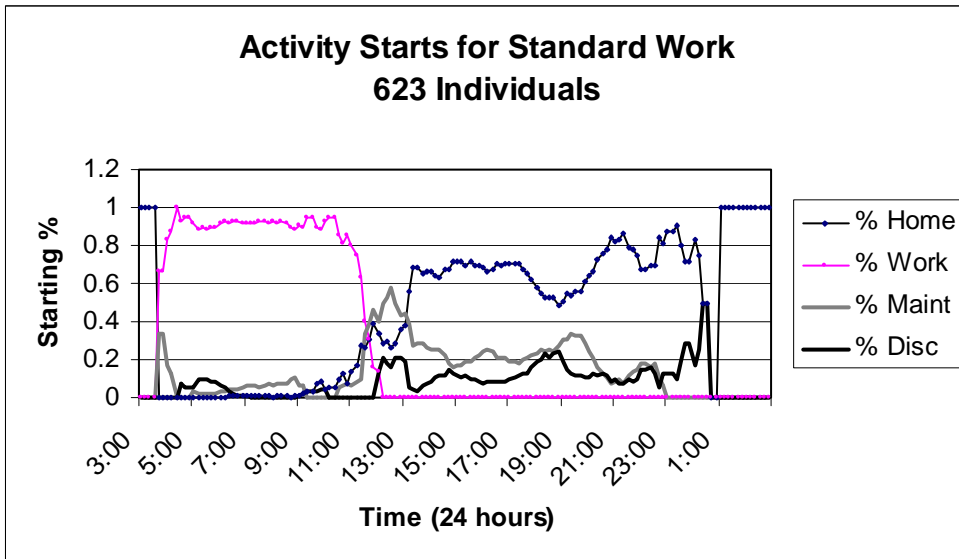


FIGURE 3 Activity Durations for Standard Work 623 Individuals

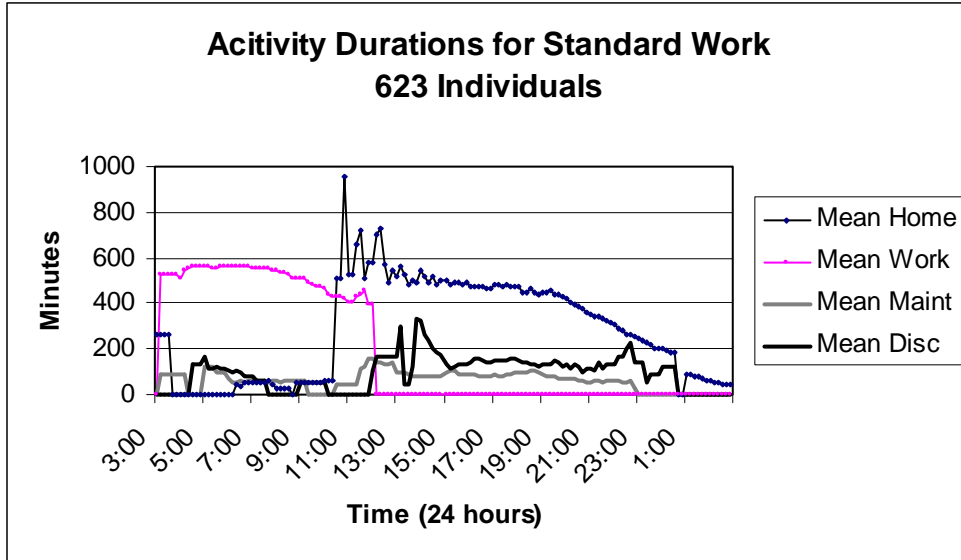


FIGURE 4 Activity Distances for Standard Work 623 Individuals

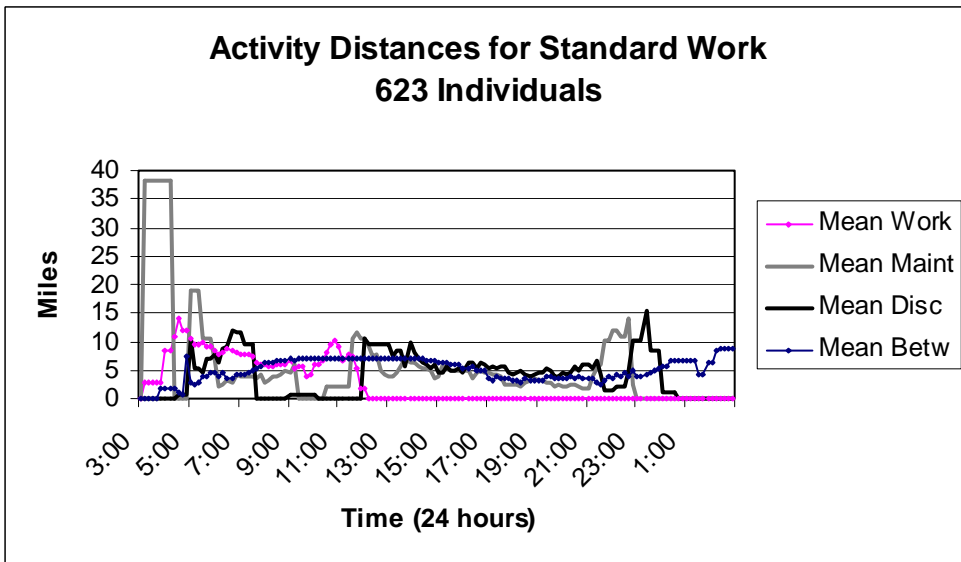


FIGURE 5 Activity Profile for Synthetic Standard Work 100 Individuals

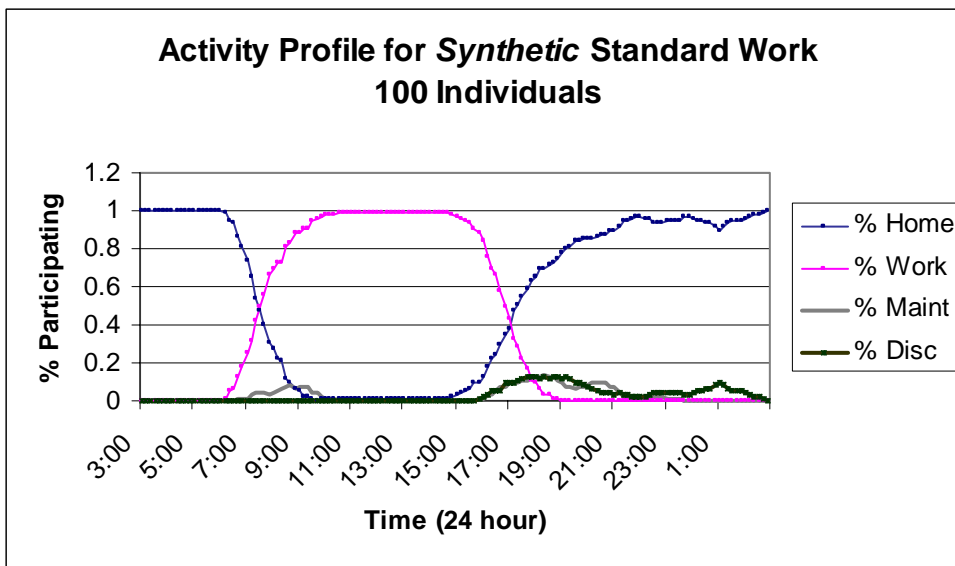


FIGURE 6 Screen Shot of the simulation approach

