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1. INTRODUCTION

This paper describes the development of SIMAP, an activity-based microsimulation model for travel demand forecasting, and is part of a larger research effort aimed at the development of innovative 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 SIMAP, the timing, sequencing, and connections between activities are explicitly included in the model 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' modeling process.

The next section describes the specifics of SIMAP. **Section 3** presents a short discussion of the aggregate activity-travel pattern classification and results. **Section 4** summarizes the implementation of the generation model, while **Section 5** demonstrates a limited application of SIMAP. Finally, **Section 6** concludes this paper by describing how this project's key contribution 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 SIMAP 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 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 will eventually replace the trip generation and distribution stages of the current travel demand modeling process.

This paper will first focus on the design issues related to the development of the modeling system and subsequently with the details of particular sub-models, though the latter may deviate as further research progresses. The foundation for this model is an aggregate classification of individual activity-travel patterns that produces a number of representative activity patterns (RAPs), groups of similar individual activity-travel patterns. The classification provides a means of identifying the choice probability distributions associated with (1) each RAP and (2) the activity type, location, and duration dimensions for each RAP. These probability distributions are derived from the observed activity-travel behavior of individual observations, which make up 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 two-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.

The first stage of SIMAP 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. The patterns output by this stage are provisional because distances are assigned only as general parameters. Initially, a household is selected from the population. For each individual household member, RAP choice probabilities are assigned. Next, 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. A drawback of the model as designed is that the process may get stuck at a time step. If an individual's pattern is ill specified in this manner, the pattern may be discarded and the entire pattern synthesis restarted for the individual. This description is only an outline of SIMAP; the specific nature of the sub models will be reviewed in more detail.

To allow the generated activity-travel pattern to reflect this activity distribution, the second stage of SIMAP 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 spatial and temporal constraints of the assigned pattern 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 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. It is believed that this is an effective approach to assigning locations.

At minimum, the activity pattern generation model can replace conventional trip generation models by converting the assigned patterns to trips. More likely, the model could replace both the trip generation *and* distribution models by producing either static (peak hour) 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 newly developed dynamic 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), SIMAP 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, SIMAP's adoption of MCS offers many modeling benefits. First, the distributions of the activity-travel patterns can be empirically derived. Second, correlations and other interdependencies can be modeled. For instance, activity durations that are correlated with the activity type can be incorporated into the simulation. Third, only a basic level of mathematics required. Forth, greater levels of precision can be achieved by increasing the number of iterations. Fifth, the model's behavior can be investigated with great ease. Sixth, it is a valid and widely recognized technique. Finally, any model changes can be compared with previous models.

3. RESULTS OF AN AGGREGATE CLASSIFICATION OF ACTIVITY-TRAVEL PATTERNS

SIMAP's approach uses as its foundation RAPs. 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 longer planning horizons (10 years).

Still, while a strong body of research has been built around RAPs, some questions still remain about applying the approach. Primarily, it is still 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 may be redundant and a full scale clustering 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 socioeconomic 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 SIMAP 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 very likely to have very 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 SIMAP, 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 cell 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 cell is deterministic as are the probabilities of participating in one of the identified RAPs for that cell. A RAP is assigned stochastically using standard simulation techniques such as MCS.

3.1 Selection of Classification Data

The classification uses first day data from the 1994 Portland Activity-travel survey to construct individual activity-travel patterns. A limited, four-type activity categorization system was used. All home activities are defined as Home. Out-of-home activities are classified into Work (any work or work-related), Maintenance (shopping or personal care, and Discretionary (social or recreational). Only individual patterns that meet the following criteria are included: (1) complete data (location and times); (2) surveyed on a weekday; and (3) at least one out-of-home activity. Further, those individual patterns meeting the criteria were split into three sets based on the characteristics of the individual: full-time employed adults (17 years of age or older), non full-time employed adults (homemakers, part-time employment, retired, etc.), and children. The actual data used consisted of 1875, 1516, and 1061 complete activity-travel patterns.

3.2 Classifying Methodology

The classification is similar to the methodology applied previously by Recker et al. (1983). Modifications from the original approach were made in calculating the distance between an activity-travel pattern and a RAP as part of the k-means clustering algorithm. Specifically, at each time step, each of the three attributes is treated as a nominal variable. 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 distance measure is incremented (otherwise, the distance 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 time step 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 distance between 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. 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 metric. Moreover, the weights associated with the three measures can easily be changed in the clustering procedure. Note, that a no travel option was present in this and all data but not part of the classification procedure and subsequent analysis presented. This omission will corrected in short order with the inclusion of a No Travel RAP for each age-employment group.

3.2 Classification Results

Adults Employed Full-time:
The classification for Adults Employed Full-time produced the following six RAPs, each with a short description of the main activity profile of the pattern:

- Standard Work - An 8 hour workday (8am - 5pm)
- Power Work - A 10+ hour workday (8am - Late)
- Late Work - A late starting (afternoon) 8 hour workday
- Work-Maintenance - Standard Work + an out-of-office noon maintenance activity
- Work-Discretionary - Standard Work + an after-work discretionary activity
- Various Short Activities - Mostly stayed home; some nearby activities for short times

The classification for Adults Not Employed Full-time produced the following four RAPs:

- Work/School - An 8 hour workday (8am - 5pm)
- Maintenance - Standard Work + an out-of-office noon maintenance activity
- Discretionary - Standard Work + an after-work discretionary activity

- Various Short Activities - Mostly stayed home; some nearby activities for short times

The classification for Children produced the following six RAPs:

- Standard School/Work - An 8 hour school/workday (8am - 5pm)
- Long School - A 10+ hour school/workday (8am - Late)
- School - Discretionary - A Standard School with an afternoon discretionary activity or activities
- Maintenance -One or more out-of-home maintenance activities (primarily a shadow of the Adult Not Employeed Full-time Maintenance RAP)
- Discretionary - One or more out-of-home discretionary activities (primarily a shadow of the Adult Not Employeed Full-time Discretionary RAP)
- Various Short Activities - Mostly stayed home; some nearby activities for short times

4. SPECIFYING SIMAP

As stated earlier, the aggregate classification of individual activity-travel patterns into RAPs provides the seeds for synthesizing activity-travel patterns. They provide a instrument for estimating the choice probability distributions associated with (1) each RAP and (2) the activity type, location, and duration dimensions for each RAP. The general outline for the pattern synthesis was described in **Section 2**. This section will document the required distributions needed to simulate synthetic patterns, the details of their construction, and an example will be developed for the Standard Work RAP of Adults Employed Full-time. **Figure 1** shows the activity profile for the Standard Work RAP.

SIMAP 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** and 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 upcoming 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.)

	Frequency	Proportion
RAP Name		
Standard Work	1261	67%
Power Work	94	5%
Late Work	53	3%
Work-Discretionary	65	3%
Work-Maintenance	129	7%
Various Short Activities	273	15%

Table A. RAP Assignment Model for Adults Employed Full-time

In order for SIMAP to produce fully specified activity-travel patterns, activities, their 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 included as part of the return Home, Work, Maintenance, or Discretionary activity.

For the duration, the average (and standard deviation) duration for each Home, Work, Maintenance, and Discretionary activity that start 30 minutes within each time step are 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 it standard deviation) can be used as sampled from **Figure 3** using a modified normal distribution.

Next, the general location has to be 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 it 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 time step when the previous activity is complete using the same techniques as above. This continues until the entire 24-hour activity-travel pattern is completed.

SIMAP 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 content are provided:

- Group RAP Table - The likelihood of engaging in an identified RAP defined by the age and employment status of the individual.
- Activity Start Table - The likelihood that given a RAP and time step, that an individual will start a Home, Work, Maintenance, or Discretionary activity.
- 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.
- 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 SIMAP is built from a set of ESRI MapObject components, providing a flexible approach for displaying, modifying, and manipulating network and land use coverages.

5. APPLYING SIMAP

A limited application of SIMAP was conducted to test of the aggregate accuracy of synthesized activity-travel patterns. SIMAP was applied to synthesize individual activity-travel patterns for the Standard Work RAPs from the socio-economic group Adults Employed Full-time. In order to construct accurate patterns, two significant changes were made to the originally developed Standard Work RAP. First, a number of patterns that consisted of a work-maintenance-work sequence were moved to the Work-Maintenance RAP. This was done because the durations of the work activity are significantly different for Standard Work and Work-Maintenance RAPs. Second, a handful of outlying late night/ early morning discretionary activities were removed from the Standard Work RAP activity engagement distributions (resulting in only Home activities beginning after 1:00 am, a very reasonable correction).

The simulation was conducted to produce 100 synthetic 24-hour activity-travel patterns that consisted of activity type, start time, duration, and distance from home. For this test, actual x-y locations were not assigned to the patterns. The aggregate activity profile (activity participation by time step) of the original Standard Work RAP activity profile

(**Figure 5**) is compared to activity profile of the synthesized patterns (**Figure 6**). 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 B**). 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 has a bias towards particular activity types. MAE and RMSE give insight into accuracy of the synthetic patterns, with RMSE more sensitive to larger error. Also calculated is the percentage of time steps the synthetic patterns are different from the observed for the ranges indicated in **Table C**.

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 C**), with the largest category being "less than 1%" within the specified activity participation range. Overall, the data indicates that the simulation framework successfully synthesizes the activity-travel patterns specified by RAPs and the distributions inherent within the RAPs.

	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 B. Calculated Error Measures of Synthesized Patterns for Standard Work

	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 C. Percentage of Time Steps Where Forecasted Participation is Within Specified Range of the Observed for Standard Work

The next step in the simulation is to add the spatial dimension to the simulation, adding both home locations and actual activity locations. Already, work is currently being done to incorporate this all-important dimension. Once this aspect of SIMAP is complete, the final stage would be to create dynamic OD tables in order to complete a working prototype of an activity-based forecasting model.

6. FUTURE RESEARCH

SIMAP 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 SIMAP framework outlined 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. The main 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 SIMAP are fairly simple allowing for ready adoption by practitioners. The current focus of the research effort is to apply the model to a geographic subarea of the Portland region or a hypothetical area based on Portland. Both transportation network and land use 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 geographic subarea selected is manageably small and contains all households under consideration. This will be a crucial test of the model.

Several potential deficiencies in SIMAP will be addressed after completion of the working prototype. The first is that 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. 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 be treated with more sophistication. It is possible to include travel as a simulated activity, though the nature of the simulation may lead to inappropriate travel. Or, travel could be implicitly attached to each out-of-home activity and included onto the duration of out-of-home activities. Finally, validation procedures need to be developed. A straightforward approach to test the methodology would be to simulate individual activity-travel patterns for a holdout sample and compare them to the actual patterns of the individual.

7. ACKNOWLEDGMENTS

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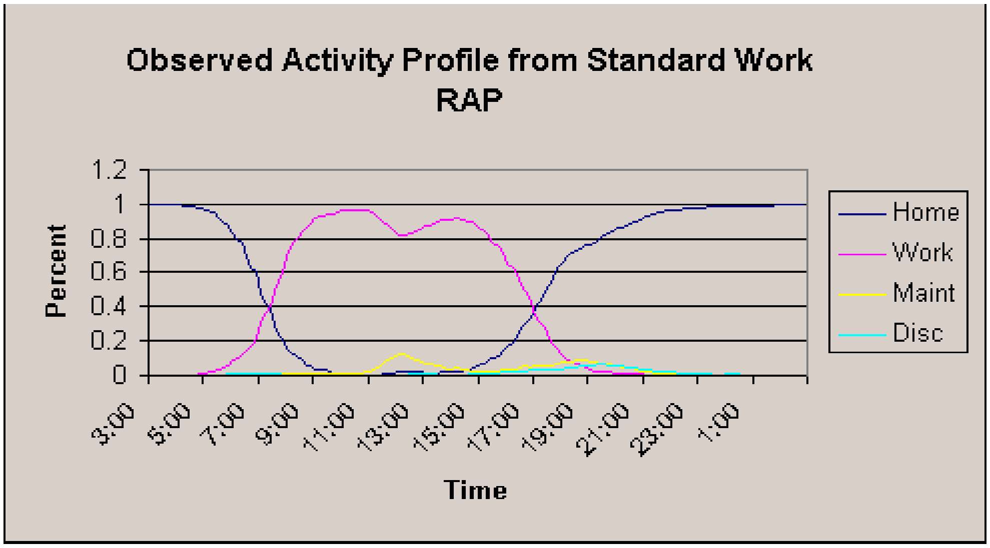

FIGURE 1.

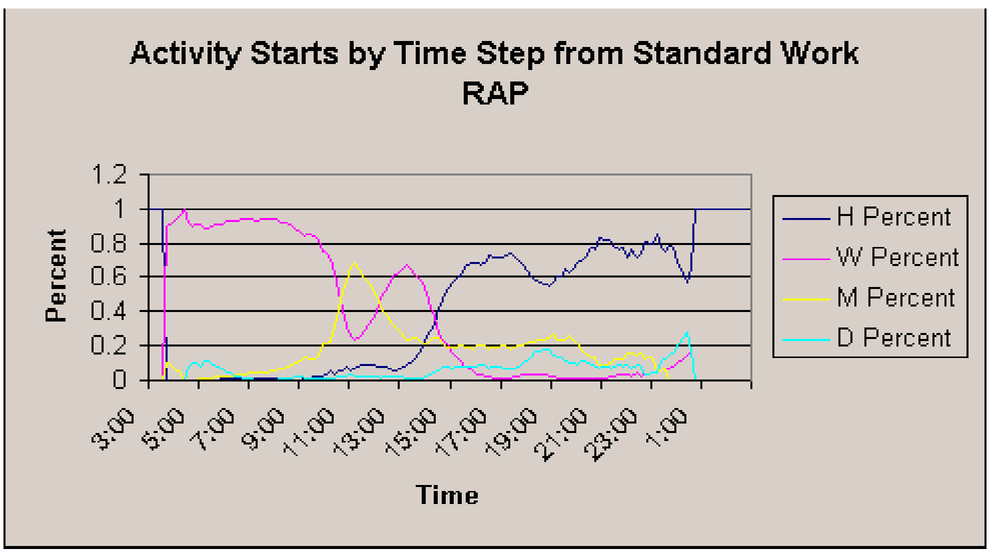

FIGURE 2.

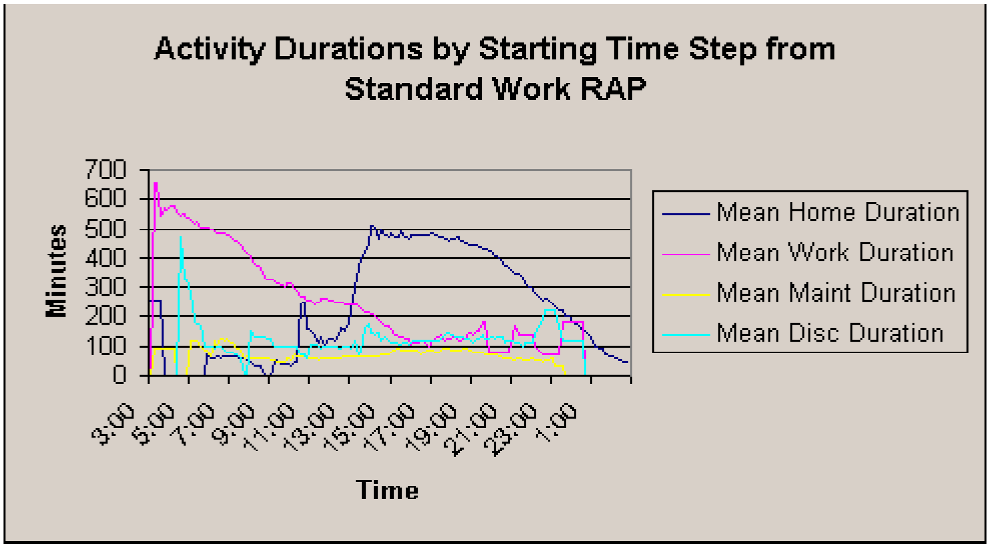

FIGURE 3.

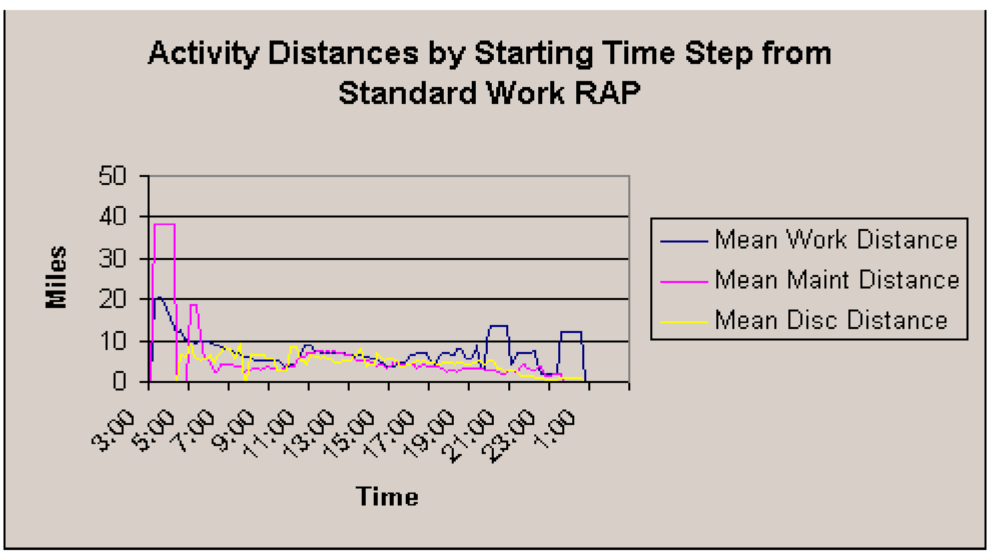

FIGURE 4.

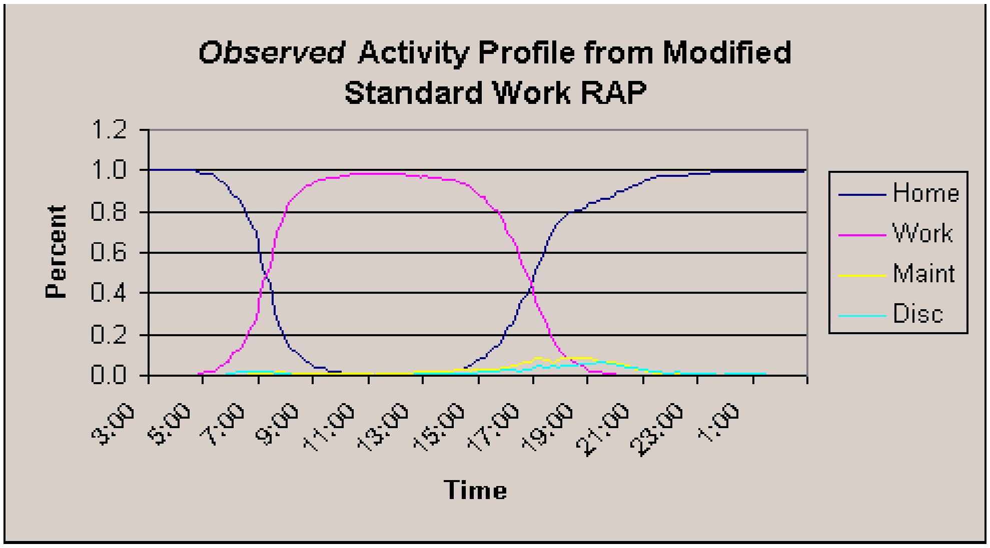

FIGURE 5.

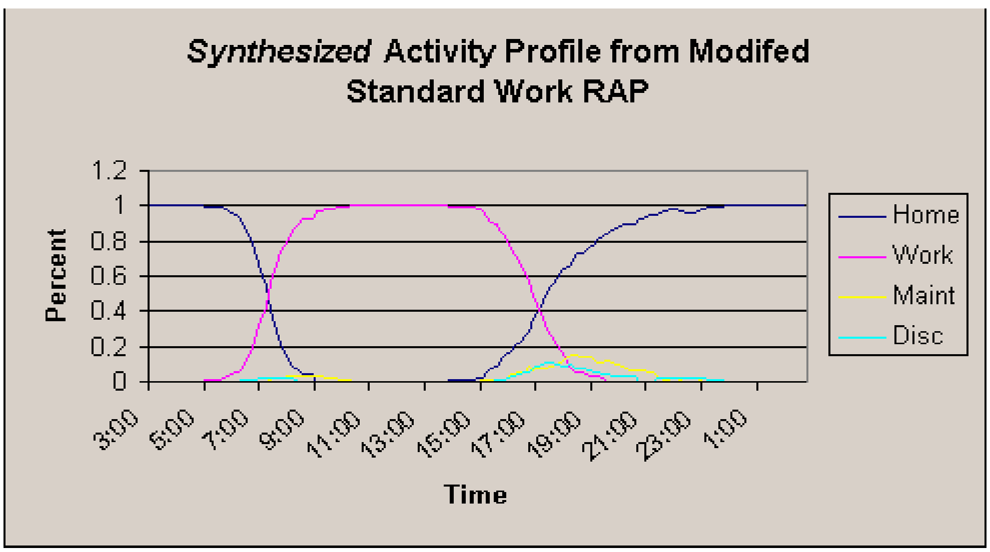

FIGURE 6.