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Modeling Activity Pattern Generation and Execution

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MODELING ACTIVITY PATTERN GENERATION AND EXECUTION

DISSERTATION

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DOCTOR OF PHILOSOPHY

IN

TRANSPORTATION SCIENCE

BY

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The dissertation of Anup A. Kulkarni

is approved and is acceptable in quality and

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CURRICULUM VITAE

Anup A. Kulkarni

EDUCATION
Ph.D. in Transportation Science Winter 02,University of California, Irvine
M.S. in Transportation Engineering June 96. University of California, Irvine
B.S. in Civil Engineering June 93. University of California, Irvine

EXPERIENCE
Transportation Analyst: 7/01 – Present; Orange County Transportation Authority
Worked as a key engineer on a number of traffic microsimulation projects on arterial streets, transit, and highways. Primary duties involved developing networks, algorithms, and models to evaluate a number of alternatives.

Software Engineer: 8/00 – 7/01: BlueKite.com
Worked as a key engineer of the Future Technology Group. Primary duties involved developing software, network test environments, and models to optimize BlueKite's client-server software for wireless communications. Key tasks included programming (C++, Perl), database construction, and project management. Acquired a clear understanding of computer networking and Internet protocols (HTTP, TCP/IP, and UDP).

Graduate Student Researcher 5: 1/97 – 7/00; University of California, Irvine
Developed an activity-based approach with the potential to replace the current generation of travel demand forecasting models. The model's aim is to simulate 24-hour activity-travel patterns that reflect actual land uses and travel networks for households in a sub-area. The system is developed using a combination of Visual Basic and C++, integrated with a GIS using ESRI's MapObjects product. The model is calibrated and tested using the Portland 1994 Activity and Travel survey.

Graduate Student Researcher 4: 8/96 – 12/96; University of California, Irvine
Ran the Irvine Transportation Analysis Model for 1995. Used TRANPLAN to extract an Irvine sub-area network and obtain Origin-Destination Matrices. Used CONTRAM and COMEST to update the OD volumes based on collected traffic count data to obtain real time (ten minute) Origin-Destination Matrices for the sub-area for input into PARAMICS traffic simulator.

Graduate Student Researcher 3: 7/94 – 7/96; University of California, Irvine
Used a GIS to analyze and extract sub-area network and land use information from Orange County. Developed a methodology to classify the extracted networks using a variety of econometric techniques, including cluster analysis and hypothesis testing. Developed a program to analyze household travel behavior in the classified sub-areas using the 1991 Southern California Association of Governments Travel Survey. Used both traditional trip-based and newer activity-based techniques to further study

differences in travel-activity behavior in the different network and land use structures. Authored and presented much of this research in journals and conferences.

Graduate Student Teaching Assistant; 3/95 – 6/95; University of California, Irvine
Managed Traffic Engineering and Transportation Forecasting courses. Led discussions sessions, homework assignments and grading. Organized two projects. The first to obtain traffic counts, find the capacities of intersections in an arterial, and determine the level of service of a system of intersections. The second project was setup6tt to demonstrate students to the 4-step planning process.

Engineering Technician; 6/93 – 8/94; City of Anaheim
Studied, analyzed and modified traffic signal timing on major routes throughout the city to improve traffic flow. Applied advanced ITS techniques and strategies to manage heavy city traffic demands in Anaheim's Traffic Management Center. Prepared and documented local time-based signal timing plans for NEMA controllers. Controlled and monitored traffic signal system during both normal and special events operation. Interacted with consultants, citizens, and other engineers on the behalf of the City. Used TRANSYT-7F to coordinate signals.

Engineering Technician; 6/91 – 10/91; County of Orange
Provided engineering and surveying support to the County staff as well as public. Provided drafting support to the surveying staff using both manual drafting techniques and AutoCAD. Checked and corrected preliminary topographic maps submitted by contractors to the County. Trained two other Engineering Technicians.

Council Member; Engineering Representative; 6/94 – 6/95; UCI Associated Students

PUBLICATIONS AND PRESENTATIONS

Kulkarni, A.A., Wang, R.M., and McNally, M.G. (1995). "Variation of Travel Behavior in Alternative Network and Land Use Structures", *Compendium of Technical Papers, 65th Annual Meeting of the Institute of Transportation Engineers*, Denver, pp.372-376.

Kulkarni, A. and McNally, M.G. (1997). "Land Use, Transportation Networks, and Travel Behavior: An Empirical Assessment", paper presented at the *Western Regional Science Association Annual Meeting*, Kona, Hawaii, February 1997.

McNally, M.G. and Kulkarni, A.A. (1997). "An Assessment of the Interrelationships between Land Use-Transportation System and Travel Behavior", paper presented at the *76th Annual Meeting of the Transportation Research Board*, Washington, DC.

McNally, M.G. and Kulkarni, A.A. (1997). "An Assessment of the Interrelationships between Land Use-Transportation System and Travel Behavior", *Transportation Research Record*, 1607, 105-115.

Kulkarni, A. and McNally (2000). "An Activity/Travel Pattern Generation Model", paper Presented at the *Western Regional Science Association Annual Meeting*. Kauai, Hawaii.

Kulkarni, A. and McNally (2000). "An Activity-Based Microsimulation Model for Generating Synthetic Activity-Travel Patterns: Initial Results", paper presented at the *IATBR 2000 Conference*. Brisbane, Australia.

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ABSTRACT OF THE DISSERTATION

MODELING ACTIVITY PATTERN GENERATION AND EXECUTION

BY

ANUP A. KULKARNI

Doctor of Philosophy in Transportation Science

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Dr. Michael McNally, Chair

Activity-based approaches are perhaps the most promising alternative to the current travel forecasting methodology. This dissertation first presents a pattern generation model that can serve as a link between activity and trip-based methodologies. The model uses a clustering approach to identify groups of similar activity-travel behavior and relates them to household socioeconomic attributes. Minimally, the pattern generation model is offered as a possible replacement to the standard trip generation model. This initial model is then expanded to serve as the core component of a proposed activity-based microsimulation model that constructs complete origin-destination tables using a wholly activity-based approach. The techniques developed provide due diligence to the complex nature of activity-travel behavior in terms of spatial and temporal constraints, household interactions, and the derived nature of such behavior. A successful application of the expanded model is outlined using data from the 1994 Portland activity-travel survey.

CHAPTER 1

OVERVIEW

1.1 INTRODUCTION

The current travel demand modeling process is in the process of fundamental reassessment. Modified from a set of models developed in the 1950's to evaluate future network configurations, the procedure essentially consists of four sequential stages: trip generation, trip distribution, mode choice, and route assignment see Jones (1983) for an overview). The four-step forecasting methodology functions in an acceptable manner for the network planning purposes which it was developed. However, federal requirements (Clean Air Act Amendments of 1970, 1977, and 1990) for transportation modeling have evolved from the original long-term forecasts to more short-term, policy sensitive forecasts without any modification of the forecasting models. As a result, the four-step forecasting methodology has been the subject of increasing criticism from academics, practitioners, and environmentalists as being inadequate.

A number of shortcomings in the methodology have been cited as particularly important. First, it lacks a behavioral foundation. As an example, current trip generation and destination choice models are calibrated and validated for a base year using zonal parameters such as trip generation rates and friction factors. Any policy change that results in a significantly altered transportation or land use environment (e.g., congestion pricing) are poorly reflected in these parameters and in the overall model forecasts.

Second, the conventional methodology is trip-based. That is, unlinked trip productions and attractions are estimated at an aggregate level disregarding any links between destinations, modes, and chains inherent in trips. Third, spatial, temporal, and interpersonal constraints are not imposed. Fourth, limited feedback or equilibration exists between or within the four stages; only at the assignment stage is any equilibration considered. Final model outputs such as network volume and travel time are not fully equilibrated with the generation, distribution, or mode choice stages. Lastly, there is only a limited exogenous treatment of land use, economics, and demographics.

Unfortunately these limitations and problems, while well known for a number of years, were met with initial complacency and subsequent frustration on the part of the practicing transportation planning community. The end result was little improvement in the state of the practice in demand forecasting models from the time they were first developed. However, two fairly recent court cases from the Bay area stemming from the Clean Air Act Amendments (1977 and 1990) and passage of the Intermodal Surface Transportation Efficiency Act (1991) have forced the transportation planning profession to address these shortcomings. The importance of addressing these concerns has been underscored by the federal sponsorship of the Travel Model Improvement Program. This research program is designed to improve current modeling practice and to forge a new modeling process that avoids the deficiencies of conventional forecasting methods and meets the conditions dictated on travel demand models by the stringent legislative and judicial modeling requirements.

The consensus among researchers is that, at a minimum, future forecasting models must provide as output detailed travel information with trip start and ending times, elapsed time between successive trips by vehicle, vehicle type associated with travel, and any day-to-day or seasonal variations in travel demand. Some of the more desirable features (not necessarily mandatory) have also been identified (Kitamura, 1996):

- activity engagement mechanisms
- consistency in movement in the Hägerstrand "constraint" sense
- a comprehensive activity itinerary
- representation of the tendencies and preferences involved in activity sequencing
- interpersonal linkages
- consideration of trip attributes

Ideally, the forecasting model developed should have the potential to deal with emergent behavior that need not be pre-defined into the model (e.g., the emergence of telecommuting as an option to commuting to work). As part of this effort to address the shortcomings of the four-step planning process, the Federal Highway Administration in 1992 solicited proposals to redesign the travel demand forecasting process and eventually recommended that (1) the current trip-based model framework be replaced by an activity-based framework, (2) microsimulation techniques be employed to expand travel and activity decisions to an urban area, and (3) geographic information systems be the platform upon which to build any system (Spear, 1994).

The activity-based approach emerged from researcher's 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, 1970). The following is a summary of the major characteristics of the activity-based approach (McNally, 1996):

- travel demand is derived from activity participation
- activity participation involves generation, spatial choice, and scheduling components
- activity and travel behavior are delimited by temporal and spatial constraints
- linkages exist between activities, locations, times, and individuals
- a number of decision paradigms are probable

Therefore, much of the need for the research presented in this dissertation follows the recommendations of the TMIP and aims to incorporate the major characteristics of the activity-based approach into operationalizing such a model.

1.2 RESEARCH HYPOTHESES

The research builds on two findings from previous research. First, it has been shown that activity patterns can be identified using standard classification techniques such as clustering. There have been a number of clustering techniques used successfully and they will be reviewed in more detail in the following chapter. Next, that activity-travel patterns are constant over time. That is, patterns estimated in a base year can used to forecast into the future as the different patterns because of this stability, in the same manner that trip generation rates are stable.

Given this foundation, three main hypotheses are considered as the core of this dissertation. First, that activity-travel patterns can be used in travel demand models much the same way as trip generation rates are used today. Current trip generation models relate socio-demographic data to trip generation rates via classification models. Identified activity patterns (or a range of patterns) can be assigned to individuals in a similar fashion. Second, 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. Third, that Monte Carlo methods can be used to simulate synthetic patterns from the choice probability data. There are a number of ways to proposed to accomplish this task and it will be a key to the success of the research. All three hypotheses will be examined in detail further through the remainder of the dissertation.

1.3 ORGANIZATION OF THE DISSERTATION

Chapter 2 presents a brief review of prior work in activity-based approaches. Although the focus is to provide a general analysis, it will also help the reader appreciate the need for research in this field. The third chapter presents a detailed discussion on the methodology of the dissertation. The fourth chapter presents some of the results of representing and classifying activity patterns to identify RAPs, the motivation for applying the classification, and the particulars of the application. Further, each identified RAP will be reviewed in relation to its members, the travel behavior apparent in the group, and the differences from other RAPs. The database used in this section consisted primarily of the 1994 Portland Activity Travel Survey. The fifth chapter discusses the implementation of the simulation approach. Tests are conducted to determine the validity of the approach and the model is applied for a small, but representative subsection of the population. This sections database consisted of transportation and land use data from the Portland Metropolitan area. The sixth and final chapter places the results of the analysis in perspective. The results are evaluated in terms of their effectiveness as possible replacement to the models currently in use. Conclusions are presented on the basis of these and future research directions are provided.

CHAPTER 2

A REVIEW OF THE LITERATURE

An activity-based model is defined as a model that attempts to describe any or all aspects of activity participation and includes constraints and linkages as noted by McNally. Minimally, activity-based models must enumerate activity and travel start and ending times, durations, locations, and associated in a time-dependent fashion (activity-travel patterns or multiple tours). During the past two decades, empirical research in this area has established the activity-based approach as the paradigm for the next generation of travel forecasting models. Readers interested in a more detailed overview of this research are directed to the reviews by Kitamura (1996).

The following sections will review some common models that have been proposed to generate activity patterns. Two distinct paths exist in developing activity-based forecasting models: optimization and simulation. Optimization models work on the principle that individuals either select or generate an activity-travel pattern that optimizes some variable (i.e., travel time) or a function of variables (i.e., utility-based econometric models). The general advantages of using such models are that they are, in theory, easy to understand and have a strong set of available solution techniques that have been developed over a number of years. Unfortunately, such models are not necessarily well-accepted as the basis of generating activity patterns given the complex nature of activity pattern generation. Nonetheless, the models developed in this area are an important part of the overall landscape and offer insight into the process.

2.1 OPTIMIZATION MODELS

2.1.1 Household Activity Pattern Program

Recker (1995) presents the household activity pattern program that optimally (travel time minimization or emissions minimization) solves the space-time paths for members of a household given an agenda of out-of-home activities. The model is constructed as a mathematical program, adapted from the formulation of the pick-up and delivery problem with time windows. Initial versions of the model were solved optimally using a restricted set of constraints. Extended versions including more intricate constraints (such as ridesharing) have also been developed, though the difficulty of the problem has resulted in the use of heuristic solution methods. Though the model's solution procedure is both complex and time-consuming, the formulation has been shown to allow for some very useful policy tests. However, it lacks an activity generation mechanism to allow for forecasting.

2.1.2 Bowman And Ben-Akiva

A number of discrete choice models have been developed to model the activity-travel pattern choice, including that of Bowman and Ben-Akiva (1995). The approach selects a utility maximizing choice of activity-travel patterns using a nested logit structure by first selecting primary tour and second the number and type of secondary tours, conditional on the first choice. The model is limited in that all the relevant choices available to a decision maker can not be specified given the large number of possible activity-travel patterns and the restricted nature of its spatial and temporal detail. Because its structure allows it to be integrated into conventional travel demand models in a straightforward manner, this model is being applied in Portland as part of the federal model development effort. A more general concern regarding optimization frameworks is their applicability to model activity-travel pattern engagement. Specifically, there is some doubt as to the ability of individuals or households to maximize some (utility) function when making such a complex choice. As a result, microsimulation approaches have been developed and popularized as alternatives to the general optimization framework.

2.2 MICROSIMULATION MODELS

Microsimulation consists of a wide range of techniques that attempt to replicate the complex individual or household level behavior of a system. Miller and Salvini (1998) defines behavior that is difficult to forecast and stems from decision rules, interactions, path dependencies, or the stochastic nature of endogenous processes (such as activity demand and travel participation) as complex. Unlike optimization approaches, no equilibrium state is assumed to exist because of the system's path dependencies and openness to time varying exogenous factors. Rather, this complexity has resulted in the use of computer-based microsimulation algorithms as a practical method for modeling the behavior, in this case the future activity-travel behavior of individuals or households over time.

Microsimulation can be combined with sample enumeration to develop a powerful forecasting procedure (though this technique is not limited to microsimulation). Miller and Salvini (1998) believe this combination to be very efficient and effective and describes the basic approach as applied in conjunction with an activity-based forecasting model:

> In this procedure...an activity-based model which predicts the number of out-of home activities in which a worker will participate [has been developed]. A representative sample of decision-makers typically exists....The short-run impact of various policies which might be expected to affect activity scheduling and trip chaining can then be tested by 'implementing' a given policy, and then using the model to compute the response of each individual to this policy. Summing up the responses of the individuals provides an unbiased estimate of the aggregate 'system' response to the policy in question.

In this method, it is assumed that (1) a representative sample population is available, (2) the sample is valid over the short time period of interest, and (3) the sample is appropriate for testing the policy of interest. In cases where the sample in question is no longer appropriate (it becomes unrepresentative or fails to include enough of an affected population) or does not exist (applying the model to a new urban area), one can be synthesized using recently developed algorithms (Beckman et al., 1995).

To avoid confusion, this proposal considers as activity-based microsimulation any forecasting approach that explicitly models daily or multi-day activity-travel behavior at an individual or household level of decision-making in a manner that addresses its complex and stochastic nature through computer-based algorithms. Recent microsimulation models have been developed or proposed that can be broadly classified as computational process models (CPM) and non-CPM models, both to be discussed in the next two sections.

2.3 COMPUTATIONAL PROCESS MODELS

In response to the complexities of the optimization models and their shortcomings, CPM's have become a suggested alternative. CPM's attempt to model the interrelated and multifaceted decisions involved in individual and (preferably) household decisions involved in activity scheduling. While some researchers limit the inclusion of models that use only heuristic rules into this category, this review allows models that use optimization rules as long as it is theorized that decisions are made on that basis.

2.3.1 STARCHILD

CPMs attempt to represent the cognitive processes that are present in activity-travel pattern formation. According to Kitamura (1996), such models attempt to capture the decision-making involved in activity-travel pattern formation rather than adopt an overriding behavioral paradigm, though many CPMs do contain some utility maximizing components. One of the first CPMs was the STARCHILD modeling system (Recker et al., 1986a and 1986b) to produce individual activity schedules given a set of observed activities. Input to the STARCHILD system includes all planned activities, travel times between home and the planned activities, and activity timing constraints. Combinatorial and sampling algorithms are employed to produce a large number of possible activity-travel (note that STARCHILD does not produce the exact solution to the problem, but an approximation because the number of possible activity-travel patterns considered are explicitly limited). This set of patterns is reduced into a number of distinct types using pattern recognition techniques. Finally, a single pattern engagement utility function is estimated based on all the observed activity-travel patterns is specified and is used to select the utility-maximizing activity-travel pattern for the individual under consideration given the reduced pattern choice set. The model is limited in that activity-generation is not explicitly modeled. Moreover, it is not entirely clear how the model can be expanded to account for a synthetically generated population due to this deficiency. The system attempts find a utility maximizing activity schedule of an individual given a set of observed activities.

2.3.2 AMOS

AMOS is a CPM designed to schedule individual activities from a set of options generated using a variety of neural network, simulation, and time allocation models Kitamura (1996). The system is policy sensitive using stated-preference data as part of the response option generator calibration. A modest policy test showed that AMOS is capable of modifying existing activity-travel patterns given various policy changes. However, AMOS also lacks a true activity generation routine and questions remain as to the details regarding the use and calibration of the models and the validity of the revealed preference models.

2.3.3 PCATS

PCATS (Kitamura, 1996) and PCATS-RUM adopt a daily activity-travel pattern as its basic unit of analysis and defines open and blocked time periods within the pattern. Activity engagement and travel decisions are simulated at the beginning of each open period using a series of probabilities conditioned on the type, location, mode, and duration of previous activities. A number of nested-logit and hazard models are used to estimate the type, location, mode, and duration of activities. Critical problems with the PCATS and PCATS-RUM approaches include the discrete treatment of duration and time-of-day employed; some concern also exists regarding the sequential modeling system and the possibility that it may produce unlikely activity-travel patterns. These problems limit the usefulness of the overall approach in specifying complete activity-travel patterns, an element required for input into emissions models.

2.3.4 OTHER CPMS

Other CPMs of note include that introduced by Kitamura (1996) similar to PCATS and PCATS-RUM, SMASH (Ettema et al., 1993) and SCHEDULER (Garling et al., 1994a). While the CPM frameworks have been extensively researched, they are quite problematic. CPMs that aim to describe the process of activity generation to pattern execution; any model system that could do so would be making a quantum leap in the state of the art in a number of disciplines. Research in this area does have the potential to lead to revolutionary models. Nonetheless, CPMs that can successfully achieve the stated goal may be years away from an operational model. Another problem may be that requisite detail may have to be abstracted away for tractability (e.g., through the use of utility maximization in submodels) in order to develop working CPMs or the omission of a number of key components such as activity generation, household interaction, or execution stage dynamics. Finally, they have the very real problem of attempting to model too much complex cognitive detail. All are important issues to consider when attempting to develop CPM-centered forecasting model alternative to the four-step process that satisfy recent planning mandates.

2.4 OTHER MICROSIMULATION APPROACHES

Both McNally (1999) and Vaughn et al. (1997) have developed microsimulation models that eschew the standard CPM framework in order to avoid their shortcomings. They propose forecasting approaches based on accepted sampling techniques in order to explicitly replicate observed complex activity-travel behavior. Both models deliberately avoid the difficult task of modeling the cognitive processes involved in activity-travel decisions.

2.4.1 McNally

McNally proposes that activity-travel behavior be represented in individual daily activity-travel patterns and minimally include time of day, activity type, and distance from home components. Aggregate classification is proposed to classify the patterns into a discrete number of representative activity patterns and develop choice probabilities among them. Simulation can then be performed using identified distributions within each category to develop complete patterns. Possible activity locations are identified using a number of distance measures within a GIS and final locations specified via a Monte Carlo simulation.

2.4.2 Vaughn Et Al. (1997)

Vaughn uses a synthetically generated population and assigns observed household activity-travel patterns based on demographic similarities between the synthetic and sampled households. The household pattern's activity locations and timings are then updated to conform to the unique location of the synthetic household. The approach has much potential in that it bypasses the difficult task of activity-travel pattern generation and maintains complex intra-household constraints. The downside is that it is a descriptive rather than a predictive model and external models are required to make the method policy sensitive.

Again, both approaches aim to replicate observed distributions using accepted sampling techniques. A concern of such approaches is that they may not be used for forecasting purposes. Some of this concern has been assuaged by findings from McNally (1999) who showed that some degree of temporal stability exists between activity-travel pattern groups. That is, given a stable transportation and sociodemographic environment, the aggregate travel behavior, as defined by the activity-travel patterns, do not vary significantly over time. Therefore, models that aim to replicate observed distributions of travel behavior might be satisfactory for forecasting purposes given a stable transportation environment. Ultimately, the developed model system is envisioned to replace the trip generation and distribution steps of the four-step model and also satisfy the recently mandated transportation planning requirements.

2.5 CONCLUSION

Clearly, there are a number of fruitful directions for future models in activity-based models. However, after this survey of the current literature, the most promising seems to be the microsimulation models reviewed in the last section. This conclusion is made precisely because no assumption is made on the complex and difficult task of modeling the thought process behind activity and travel directions. Rather, the less difficult, though still challenging task of replicating observed behavior is tackled. It is from such a starting point that this dissertation will begin to model activity-travel behavior.

This is only a broad overview of similar types of models, but additional research is reviewed at various stages of the model development. Clearly, each method for simulating activity-travel patterns offers both benefits and limitations that need to be balanced in order to develop an effective and working activity-based travel demand model. However, for this dissertation proposal, a microsimulation formulation for generating individual daily activity-travel behavior for a (real or synthetic) population is developed using an activity-based approach that replicates observed distributions of activity-travel behavior similar to McNally and Vaughn. The core of the approach is the outlined in the next chapter.

CHAPTER 3

RESEARCH MOTIVATION AND FRAMEWORK

3.1 INTRODUCTION

The primary motivation of this dissertation is to develop an activity-based simulation approach for travel demand forecasting. While there is great enthusiasm towards a shift to activity-based microsimulation models in the travel demand community, much work is needed to develop models that can generate activity participation and travel demand for a population of interest. The activity-based approach has emerged from the desire to model travel behavior by understanding the nature of the 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, 1970). 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 dissertation, 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 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.

3.2 DEFINING THE ACTIVITY PATTERN

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 (144 time steps). All out-of-home activity types are defined in the following manner: work (work, work-related, and school activities), maintenance (dine out and shopping-type activities), and discretionary (visiting friends and social party-type activities). Next, all in-home activities are characterized as home. 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 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 construct is used to reduce the complexity of characterizing a large number of activities over the 24-hours. These types of breakdowns have been shown to be useful in classifying individual activity behavior.

3.3 MODEL DEVELOPMENT

3.3.1 The Basic Model

This dissertation 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. Potential associations on characteristics of activity-travel behavior which should be considered by the activity-travel pattern generator include the following: history dependence of activity choice; time-of-day dependence of activity participation; spatial and temporal constraints; planned versus unplanned activities; travel time budgets;

prism constraints; trade-off between activity duration and travel time: and modal continuity (Kitamura 1996).

3.3.2 General MCS

Monte Carlo simulation (MCS) is a technique of randomly sampling from a specified probability distribution numerous times in a fashion that accurately represents the overall distribution. The values simulated for the model reflects the probability that the values could occur. Numerical methods that are known as Monte Carlo methods can be freely expressed as statistical simulation methods, where statistical simulation is defined in quite universal terms to be any technique that makes use of series of random numbers to execute the simulation. Monte Carlo methods have been in use for centuries, but only in contemporary decades has the system found the standing of a capable statistical method adept of tackling the largely complicated applications. Monte Carlo is currently used in many varied fields, from the simulation of complex phenomena such as stock market fluctuations and the simulation of the esoteric fission processes in high energy physics experiments, to the ordinary, such as the simulation of a monopoly game or the outcome of a game in "Jeopardy." The likeness of Monte Carlo methods to games of chance is a good one, but the "game" is a system, and the outcome of the game is not monetary but rather a possible answer to some dilemma.

3.3.3 Deriving the MCS Distributions

Specific to this model, a number of distributions need to be specified in order to develop the microsimulation proposed to produce activity-travel patterns. First, a likelihood of an individual engaging in each RAP needs to be constructed based on a combination of individual, household, neighborhood development, and pattern characteristics. A number of models could be used to estimate these likelihoods including cross-classification and discrete choice models.

Second, probability distributions are specified for RAP identified across a number of dimensions (e.g., activity type, duration of activity, and location). Distributions for a MCS can be specified in two manners. It is possible to use available data to define the fitted distribution empirically using histograms on both continuous and discrete data: or, theoretical distributions can be fitted to observed data. This approach will use the empirical method of specifying activity-travel pattern characteristic distributions. The advantage of this method is that it is intuitively simple and that the estimation and use of inappropriate or confusing theoretical distributions is avoided.

Dependencies that may exist between certain simulated characteristics need to be controlled. For instance, the duration distribution of a first work activity may be different than the duration distribution of a second work activity. This can be controlled by specifying different distributions for affected RAP. In the situation described, a simple solution could be to derive duration distributions for the first and second work activities (or more, if required).

3.3.4 MCS Step-by-Step

As constructed, 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 (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 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.

3.3.5 Deriving the MCS Distributions

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 structural model is parsimonious. Fourth, greater levels of precision can be achieved by increasing the number of iterations. Fifth, 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 further in the following chapters with a discussion of the specific nature of the sub models. 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.

3.3.6 The Simulation Deficiencies

There are several deficiencies in the proposed activity-based microsimulation approach that need to be addressed at some point. 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. However, the initial focus of the approach is to develop a working model that synthesizes individual activity-travel patterns. Only after will an effort be made into including household interdependencies. 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. Also, the standard four-step validation routines can be applied.

3.3.7 The Simulation Characterized Through Previous Research

This approach builds on the findings of past research: (1) activity participation and travel demand can be represented by activity-travel patterns using a multidimensional, time-dependent structure; (2) groups of individuals with similar activity-travel behavior exist and can be identified into representative patterns; and (3) noticeable and significant relationships exist between RAPs and a number of variables, such as individual role and socioeconomics. It is hypothesized that (1) these findings can be exploited in developing a modeling system that forecasts activity-travel patterns which accurately reflect the distributions of the distinguished activity-travel pattern groups and their internal characteristics; and (2) by relating RAPs to a number of individual and household sociodemographic, network development, and pattern characteristics, the model system can be policy sensitive.

3.4 SUMMARY

In summary, the specific components included in this dissertation include:

a) Classification of individual activity-travel patterns to identify a number of discrete RAPs.

b) Establishment of relationships between the identified RAPs to individual and household sociodemographic characteristics, network development characteristics, and pattern characteristics.
c) Estimation of activity-travel pattern choice probabilities.
d) Specification of probability distributions for a number of activity characteristics for each identified RAPs.
e) Application of a MCS of activity patterns for population of interests using (a) the pattern choice probabilities from (3), (b) the probability distributions from (4), and (c) the activity distributions for each individual household location.
f) Validation of the simulated patterns by assigning them on the household's available activity and travel environment using a GIS.

This chapter should be a clear guide of the path that is to be taken in this research. First, the basic framework of the modeling approach was described. Second, a description of the data to be used in the calibration and validation of the model were described. Finally, the hypotheses that are theorized are summarized. The next chapter starts the construction of the model be describing the classification of activity patterns and identification of RAPs.

The next chapter applies the basic framework of the modeling approach as described in this chapter to real data. The result is a classification of individual activity patterns and the identification of representative activity patterns. Second, a description of the data to be used in the calibration and validation of the model were described. The next chapter starts the construction of the model be describing the classification of activity patterns and identification of RAPs.

CHAPTER 4

CLASSIFYING ACTIVITY PATTERNS AND IDENTIFYING RAPS

4.1 INTRODUCTION

This chapter presents the methodology and results of the individual activity-travel pattern classification. It also demonstrates an application of the methodology by constructing a pattern generation model that could serve as a bridge between current trip-based methodologies and activity-based approaches being developed today.

4.2 RESEARCH APPROACH AND METHODOLOGY

4.2.1 Representation of Activity-Travel Patterns

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 the method developed by Recker et al. (1983): an individual level depiction of the activity type, distance from home, distance between last activity, mode used, and/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 can be minimally defined on activity and spatial 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).

The goal of classification is to distinguish between one or more different activity-travel pattern types. Ideally, any representation of activity-travel patterns should retain as much of the original pattern information as necessary in order to classify subpopulations in an efficient fashion. Further, it is preferable to remove as much redundant and irrelevant information that could degrade classification performance as correlated features increase the error rate. Two fairly successful attempts at specifying activity-travel patterns were Recker et al. (1983) and Pas (1983). Recker uses time-dependent activity type and distance vectors to present a three dimensional representation of an individual's activity-travel pattern. The advantage of this representation is that it can be aggregated into trip tables or used as part of air-quality models in a straightforward manner (see McNally, 1999). Shortcomings of this depiction include an emphasis on the particular sequence in which activities and travel are engaged and that individual activity-travel patterns, which are identical except for a time differential, may be classified as different. This problem may particularly affect short-run activities, as they are more sensitive to this problem of time lag rather than long run (long-run activities may still overlap during a good proportion of time increments). Possible extensions to the three-dimensional representation of activity-travel patterns may correct this limitation. An additional problem (Pas, 1983) concerns the separate treatment of "distance from home" and activity type dimensions in the analysis and then synthesizing the results. That is, there is no guarantee that each RAP is consistent with respect to the activity type for all time increments. As a result, when updating the distance measure, it could be a distance measure from any of the activity types considered. As long as enough groups are specified, past research has shown that the classification should be able to differentiate suitably even with the separate treatment of the dimensions.

Pas (1983) describes activity-travel patterns using a primary/secondary attribute approach. Out-of-home stops are defined as primary attributes; each stop then had the type of activity and the time of day as secondary attributes. A similarity index is then computed by sequentially comparing all primary and, given the existence of stops, secondary attributes of the activity-travel patterns. For instance, given two separate activity-travel patterns with two and four activities respectively, the secondary attributes of the first two activities would be compared. The approach by Pas is limited in that only discrete or discretized continuous variables can be used to describe and compare daily activity-travel patterns. These include important measures including distance and time. As a result, Pas is forced to use activity type and time of day variables to classify his patterns where more detailed secondary measures needed to be considered.

This research uses as a starting point the simultaneous, time-dependent representation first used by Recker et al. (1983) that discretized time into small intervals and identified activity-type and distance attributes at each interval. This three-dimensional representation is expanded because of the increased data requirements of forecasting models. Variables considered as part of this expansion include those that provide insight into the distance between activities, travel mode, and joint activity participation. Moreover, changes are being considered in the treatment of some variables to accommodate the proposed microsimulation, including a binary treatment of activity type. Clearly, more alterations to the representation of activity-travel patterns will be considered if needed.

4.2.2 Classification of Activity-Travel Patterns

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.

Classification involves 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 by the RAPs. By distinguishing these patterns, it is possible to deal with the complete daily activity-travel patterns of individuals in a holistic manner.

4.3 CLASSIFYING ACTIVITY-TRAVEL PATTERNS INTO RAPS

4.3.1 Selection of Classification Data

The individual activity-travel patterns from the first day data 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. As a result, a total of 3,391 adults and 1061 children 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 described in the last section: 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 activity-travel patterns, respectively.

4.3.2 Classifying Methodology

The classification is similar to the standard k-means (clustering) methodology applied previously by Recker et al. (1983). Clustering is a commonly used, unsupervised learning algorithm that groups cases into a predefined number based on the similarity in Euclidean space. Cluster analysis is a well understood and well accepted technique and will not be detailed here, though the reader is referred to Recker et al. (1983) for further details. 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, and distance between last activity defined for each time step with the "best" result being selected for further analysis based on quantitative and qualitative factors. To calculate the distance 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 timestep 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 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 distance between a particular RAP and an activity-travel pattern will range from 0 to 432 (144 timesteps * 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 metric.

Once the initial classification results are compiled, sets of rules are 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 a sense of the RAPs 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.

4.4 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 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.

4.4.1. Adults Employed Full-Time

For the full-time employed adult subset, clustering began with two groups and ended at ten groups. The RAP set selected for further analysis was determined based on the size of the groupings and a subjective analysis of their makeup. RAPs with equivalent activity-profiles, small differences in distance, and few members were combined to avoid over defining the RAPs. From the classification, five RAPs were produced that can be broadly identified in the following manner:

A1. Standard Work: A single 8 hour work activity between 8am and 5pm

A2. Power Work: A single 10+ hour work activity between 8am and late

A3. Late Work: An 8 hour workday starting in the afternoon

A4. Work-Maintenance (Multiple Work): Multiple Work activities, usually with a lunchtime out-of-office maintenance activity

A5. Various Short Activities: Multiple activities for short times nearby home

The RAP rules developed from the classification are the following:

1. If at least one (work or non-work) activity and a total work activity duration of less than 5 hours, then the pattern is classified as Various Short Activities.
2. If at least one work activity with a total duration of greater than 5 hours, and the start time of the first work activity is after noon, then pattern is classified as Late Work.
3. If *one* work activity, the start time of the first work activity is before noon, and the duration of all work activities total between 5 hours to 10 ½ hours, then the pattern is classified as Standard Work.
4. If *one* work activity, the start time of the first work activity is before noon, and the duration of all work activities total greater than 10 ½ hours, then the pattern is classified as Power Work.
5. If *two or more* work activities, the start time of the first work activity is before noon, then the pattern is classified as Work-Maintenance (Multiple Work).
6. If no out-of-home activities, then pattern is classified as a No Travel.

Figures 4.1 to 4.5 show the activity profiles for all RAPs in this data subset. Each 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 and generally provide a good snapshot of the RAP from which the above RAP descriptions can be graphically viewed. It is on this dimension that the RAPs were defined through the classification.

Tables 4.1 through 4.4 present the socioeconomic, activity, and travel statistics of each of the five RAPs as well as the overall group. For the overall group, the average age of the individuals is a little more than 40 years, 56/44 split between males and females, and 96 percent with driver's licenses. The household lifecycles of the individuals are primarily "Couples without Children" (31%), followed "Unrelated Persons" (20%), "Dual Worker Couples with Children" (18%), and "Single Person" households (16%). The households are primarily own their homes (74% vs. 26% renting), from upper middle income ($45 – $50K), and have an average household size of 2.6 (mostly two and three member households).

The Work-Maintenance RAP (A4) consists of a majority of activity-travel patterns (40 percent of all activity-travel patterns). Demographically, the individuals that made up the RAP are very consistent with the overall average, though they have the highest median income ($50K – $55K). The typical workday is very similar to the Standard Work RAP at 8 hours between 8 AM and 5 PM. The main difference is that around 35 percent of all members engage in a maintenance

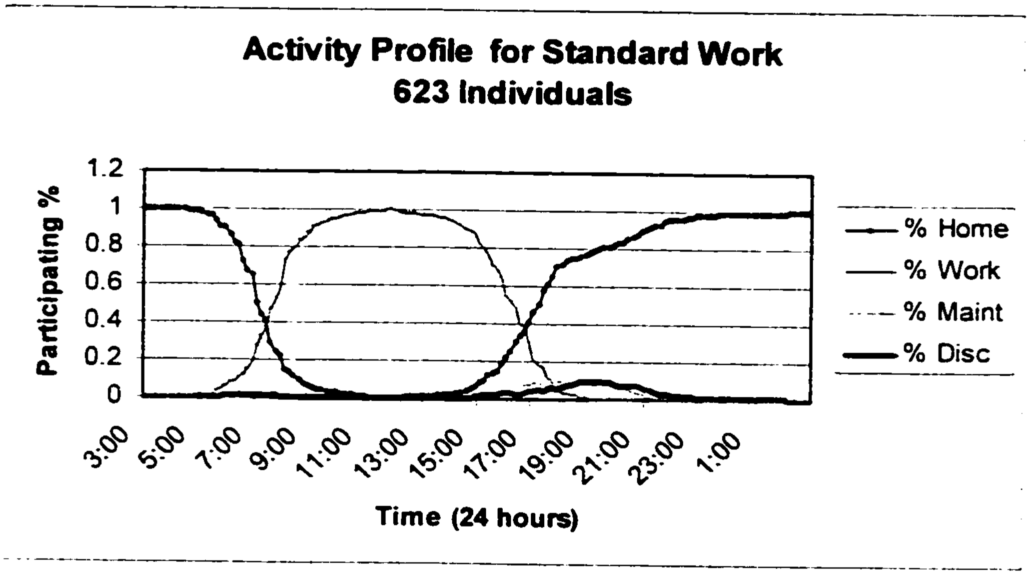

Figure 4.1 Adults Employed Full-time: Activity Profile for Standard Work RAP

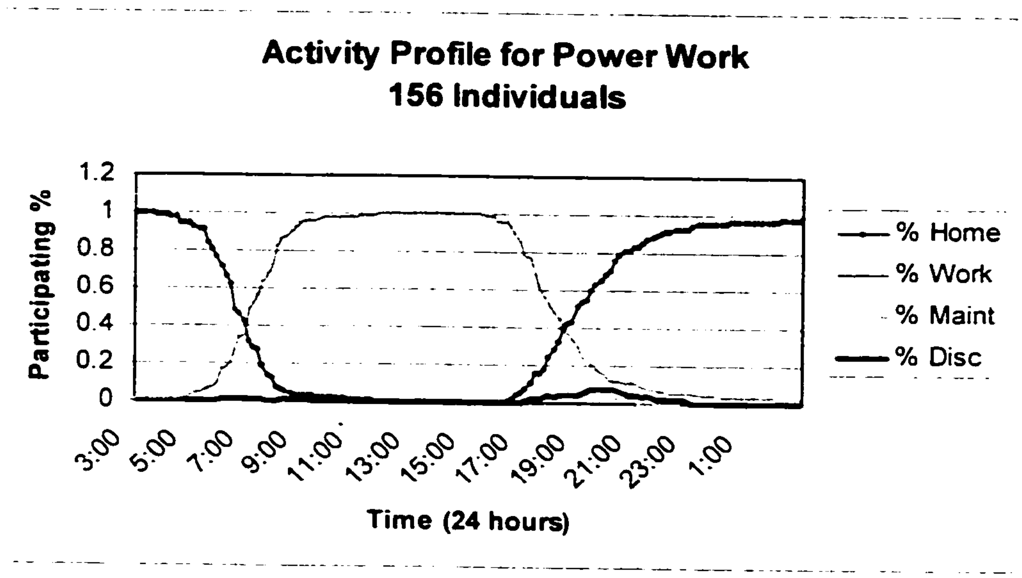

Figure 4.2 Adults Employed Full-time: Activity Profile for Power Work RAP

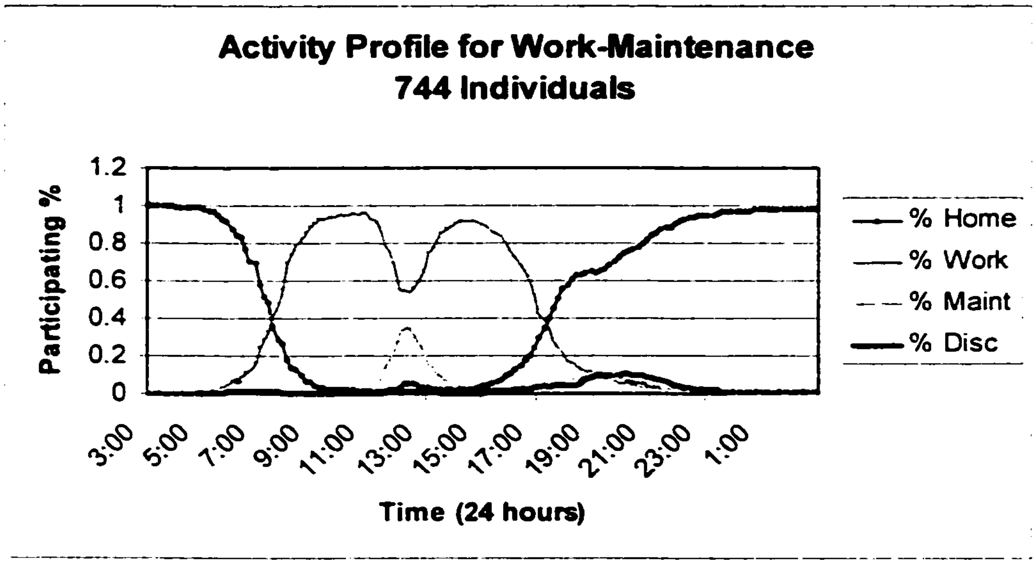

Figure 4.3 Adults Employed Full-time: Activity Profile for Work-Maintenance RAP

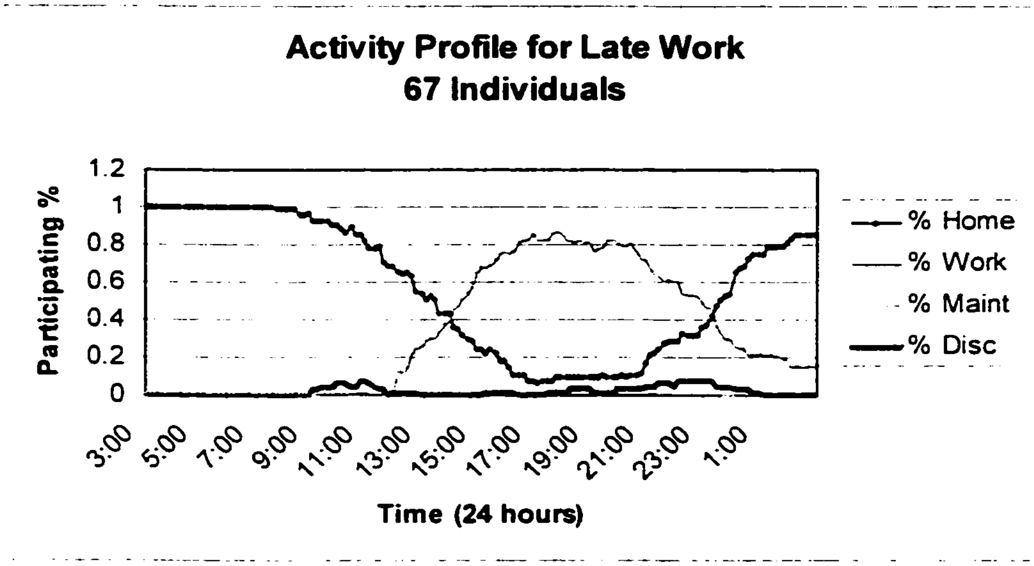

Figure 4.4 Adults Employed Full-time: Activity Profile for Late Work RAP

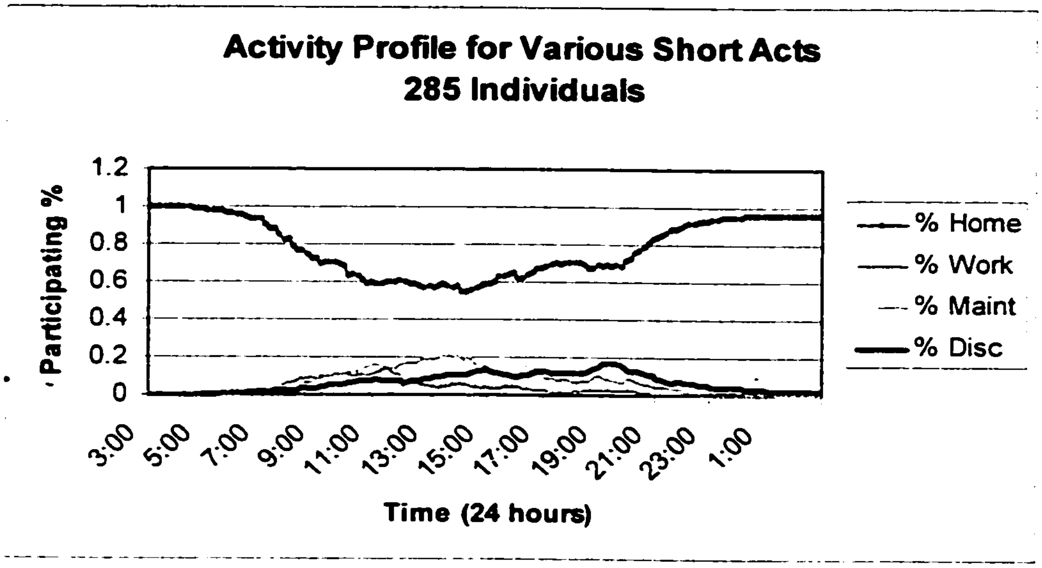

Figure 4.5 Adults Employed Full-time: Activity Profile for Various Short Acts RAP

Table 4.1a Descriptive Statistics for Adults Employed Full-time by RAP*

Variable/ RAP Group	Size		Sex			License			Homeownership		
	Freq.	Prop.		Freq.	Prop.		Freq.	Prop.		Freq.	Prop.
Standard Work	623	33%	Female Male	296 327	48% 52%	No Yes	24 599	4% 96%	Own Rent	471 149	76% 23%
Power Work	156	8%	Female Male	48 108	31% 69%	No Yes	3 153	2% 98%	Own Rent	118 36	76% 23%
Late Work	67	4%	Female Male	25 42	37% 63%	No Yes	4 63	6% 94%	Own Rent	39 26	58% 39%
Work-Maintenance	744	40%	Female Male	331 413	45% 55%	No Yes	28 716	4% 96%	Own Rent	552 189	74% 25%
Various Short Acts	285	15%	Female Male	117 168	41% 59%	No Yes	9 264	3% 97%	Own Rent	202 83	71% 29%
All RAPs	1875	100%	Female Male	817 1058	44% 56%	No Yes	66 1808	4% 96%	Own Rent	1382 483	74% 26%

* "Don't Know/Refused" replies not included in table.

Table 4.1b Descriptive Statistics for Adults Employed Full-time by RAP*

Variable/ RAP Group	Median Income	Mean Hh. Size (Sdev)	Mean Hh. Vehicles (Sdev)	Mean Age (Sdev)
Standard Work	$40K – $45K	2.7 (1.3)	2.1 (1.0)	41 (10.9)
Power Work	$45K – $50K	2.7 (1.3)	2.1 (1.0)	40 (9.5)
Late Work	$35K – $40K	2.5 (1.4)	1.7 (1.0)	40 (13.0)
Work-Maintenance	$50K – $55K	2.5 (1.4)	2.0 (1.0)	41 (10.2)
Various Short Acts	$45K – $50K	2.7 (1.2)	2.0 (1.0)	40 (10.3)
All RAPs	$45K – $50K	2.6 (1.3)	2.0 (1.0)	41 (10.5)

* "Don't Know/Refused" replies not included in table.

Table 4.2a Lifecycle for Adults Employed Full-time by RAP: Frequency and Proportion

Group/ Lifecycle	Standard Work		Power Work		Late Work.	
	Freq.	Prop.	Freq.	Prop.	Freq.	Prop.
Single Person	91	15%	19	12%	16	24%
Single Parent	19	3%	7	5%	3	5%
Couple w/o Child	191	31%	50	32%	18	27%
Single Worker Couple w/ Children	69	11%	29	19%	4	6%
Dual Worker Couple w/ Children	121	19%	19	12%	7	10%
Unrelated Persons	132	21%	32	21%	19	28%
All Lifecycles	1261	100%	94	100%	67	100%

Table 4.2b Lifecycle for Adults Employed Full-time by RAP: Frequency and Proportion

Group/ Lifecycle	Work-Maintenance		Various Short Activities		All RAPs	
	Freq.	Prop.	Freq.	Prop.	Freq.	Prop.
Single Person	138	18%	41	14%	305	16%
Single Parent	20	3%	6	2%	55	3%
Couple w/o Child	238	32%	85	30%	582	31%
Single Worker Couple w/ Children	78	11%	38	13%	218	12%
Dual Worker Couple w/ Children	129	17%	63	22%	339	18%
Unrelated Persons	141	19%	52	18%	376	20%
All Lifecycles	129	100%	273	100 %	1875	100%

Table 4.3 Activity Statistics for Adults Employed Full-time by RAP: Mean (Stdev)

Group/ Variable	Standard Work	Power Work	Late Work	Work-Maintenance	Various Short Acts	All RAPs
Num Acts	4.3 (1.5)	3.6 (1.0)	5.0 (2.0)	6.4 (1.6)	5.7 (2.6)	5.3 (2.0)
Home	2.3 (0.6)	2.1 (0.4)	2.3 (0.7)	2.5 (0.6)	2.7 (0.8)	2.4 (0.7)
Work	1.0 (0.3)	1.1 (0.3)	1.5 (0.7)	2.2 (0.6)	0.4 (1.0)	1.4 (0.9)
Shop Gen.	0.2 (0.5)	0.1 (0.3)	0.3 (0.5)	0.3 (0.6)	0.7 (0.9)	0.3 (0.6)
Shop Oth.	0.0 (0.0)	0.0 (0.0)	0.0 (0.1)	0.0 (0.0)	0.0 (0.1)	0.0 (0.0)
PB	0.1 (0.4)	0.0 (0.2)	0.1 (0.3)	0.2 (0.5)	0.4 (0.7)	0.2 (0.5)
Soc/Rec.	0.3 (0.6)	0.2 (0.4)	0.2 (0.5)	0.3 (0.6)	0.7 (1.0)	0.3 (0.7)
Dine Out	0.1 (0.4)	0.1 (0.3)	0.4 (0.6)	0.9 (0.6)	0.4 (0.6)	0.5 (0.6)
School	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.1 (0.2)	0.0 (0.1)	0.0 (0.1)
Serve	0.2 (0.5)	0.1 (0.3)	0.2 (0.6)	0.2 (0.5)	0.3 (0.7)	0.2 (0.5)
Chgtrvl.	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Duration						
Home	13.3 (1.9)	11.1 (1.7)	13.7 (2.0)	12.5 (2.0)	19.0 (3.8)	13.6 (3.2)
Work	8.4 (1.6)	11.2 (2.0)	7.8 (2.0)	8.4 (1.6)	0.7 (1.4)	7.4 (3.4)
Shop Gen.	0.1 (0.4)	0.1 (0.2)	0.2 (0.5)	0.1 (0.4)	0.6 (0.9)	0.2 (0.5)
Shop Oth.	0.0 (0.0)	0.0 (0.0)	0.0 (0.2)	0.0 (0.0)	0.0 (0.5)	0.0 (0.2)
PB	0.1 (0.4)	0.0 (0.1)	0.1 (0.3)	0.1 (0.5)	0.4 (1.0)	0.1 (0.6)
Soc/Rec.	0.5 (1.2)	0.3 (0.8)	0.5 (1.1)	0.5 (1.1)	1.6 (2.8)	0.6 (1.6)
Dine Out	0.2 (0.7)	0.1 (0.3)	0.3 (1.0)	0.7 (0.8)	0.6 (1.5)	0.5 (0.9)
School	0.1 (1.0)	0.1 (0.8)	0.1 (0.6)	0.2 (0.8)	0.0 (0.5)	0.1 (0.8)
Serve	0.0 (0.1)	0.0 (0.1)	0.0 (0.2)	0.0 (0.1)	0.1 (0.4)	0.0 (0.2)
Chgtrvl.	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Travel	1.3 (0.7)	1.2 (0.6)	1.3 (0.9)	1.5 (0.8)	1.3 (0.9)	1.4 (0.8)

Table 4.4 Travel Statistics for Adults Employed Full-time by RAP: Mean (Stdev)

Group/ Variable	Standard Work	Power Work	Late Work	Work-Maintenance	Various Short Acts	All RAPs
Number Trips	3.2 (1.5)	2.6 (1.0)	3.4 (1.9)	4.5 (2.2)	4.5 (2.5)	3.9 (2.0)
HBW	1.6 (0.6)	1.7 (0.5)	1.6 (0.6)	1.9 (0.9)	0.7 (1.0)	1.6 (0.9)
HBO	1.0 (1.2)	0.5 (0.8)	1.1 (1.3)	0.9 (1.0)	2.7 (1.8)	1.2 (1.4)
NHBNW	0.2 (0.7)	0.3 (1.0)	0.2 (0.7)	0.2 (0.7)	0.9 (1.3)	0.3 (0.8)
NHBW	0.4 (0.6)	0.1 (0.3)	0.4 (0.8)	1.4 (1.3)	0.3 (0.8)	0.8 (1.1)
HBS	0.0 (0.3)	0.0 (0.2)	0.0 (0.2)	0.1 (0.4)	0.0 (0.2)	0.1 (0.3)
HBC	0.0 (0.0)	0.0 (0.7)	0.0 (0.3)	0.0 (0.0)	0.0 (0.2)	0.0 (0.0)
Vehicle	2.8 (1.7)	2.3 (1.4)	2.8 (2.0)	3.7 (2.1)	3.9 (2.7)	3.3 (2.0)
Transit	0.2 (0.4)	0.1 (0.4)	0.3 (0.9)	0.2 (0.7)	0.1 (0.5)	0.2 (0.6)
Ped.	0.2 (0.6)	0.2 (0.4)	0.3 (0.8)	0.6 (1.3)	0.5 (1.2)	0.4 (1.0)
Work	1.0 (0.2)	1.0 (0.2)	1.1 (0.4)	1.8 (0.9)	0.4 (0.8)	1.2 (0.8)
Maint.	0.7 (1.0)	0.3 (0.6)	0.8 (1.1)	1.0 (1.1)	1.8 (1.6)	0.9 (1.2)
Disc.	0.3 (0.6)	0.2 (0.4)	0.2 (0.5)	0.3 (0.5)	0.6 (0.9)	0.3 (0.6)
Home	1.3 (0.6)	1.1 (0.4)	1.3 (0.7)	1.4 (0.6)	1.7 (0.9)	1.4 (0.7)
AM PK	0.6 (0.7)	0.3 (0.6)	0.1 (0.5)	0.7 (0.6)	0.5 (0.7)	0.6 (0.7)
MD	0.6 (0.8)	0.1 (0.3)	1.8 (1.5)	1.5 (1.2)	2.3 (1.9)	1.2 (1.4)
PM PK	1.1 (0.9)	0.9 (0.7)	0.4 (0.7)	1.3 (0.9)	0.9 (1.1)	1.1 (0.9)
OP	1.0 (1.0)	1.2 (0.7)	1.1 (0.6)	1.0 (1.0)	0.8 (1.0)	1.0 (1.0)

activity (most probably dining out) between noon and 1:30 PM. The work activity's average distance from home is 9 miles.

The Standard Work RAP (A1) consisted of the second largest group of activity-travel patterns (33%) and correlated very well with the overall group's socioeconomic statistics. Most members executed a traditional workday comprising of an AM-peak commute to a conventional 9 hour (8 hours work and 1 hour lunch) work activity, and a return home trip in the PM-peak. All engaged in only one work activity, though roughly 10 percent of the RAP members exhibited some after-work maintenance or discretionary activity (dining out). The work activity's average distance from home is 7 miles.

The Various Short Activities RAP (A5) makes up the third largest group at 15 percent and again, is similar to the overall RAP socio-economics. The only statistic that stands out is the large proportion of "Dual Worker Couples with Children" lifecycle (22%) that makes up the RAP. The typical day consists of a number of different activities with short durations. Activity statistics suggest that likely activities include shopping (grocery, clothes, etc.), personal business, and social/recreational. Interestingly, an individual in the RAP makes 4.5 trips, compared with 3.9 trips for the average "Adult Employed Full-time", indicating that full-time workers who stay home make more trips than when they go to work. A majority of the trips in this RAP are sandwiched between the AM and PM-peak hours and averaging less than 3 miles from home.

The Power Work RAP (A2) consisted of 8 percent of the activity-travel patterns. It has the largest proportion of males (69%), largest proportion of drivers license owners (98%) and largest proportion of home owners (76%). The makeup of the RAP contains a larger than average proportion (19% vs. 12%) of the family's primary wage earner (i.e. "Single Worker Couples with Children") and a lower than average proportion of "Dual Worker Couples with Children". The typical pattern contains only one work activity and is 2 hours longer than the Standard Work RAP at 10 hours and the typical work day between 8 AM and 9 PM, including possible maintenance or discretionary activities while at work (possibly a lunch or dinner activity). The work activity's average distance from home is 7 miles.

The Late Work RAP (A3) consists of the least number (4%) of activity-travel patterns. The individuals that made up the RAP are consistent with the overall average in most categories, though they have a higher proportion of the "Unrelated Persons" lifecycle group (28% vs. 20%) and a lower proportion of "Dual Worker Couples with Children" (10% vs. 18%) than the overall average. It has the second largest proportion of males (63%), and largest proportion of renters (39%), and the lowest income classification ($35K – $40K). A majority of the individuals have no children, consisting largely of the "Unrelated Persons" (28%), "Couples w/o Children", and "Single Persons" lifecycles. Most members execute an 8-½ hour work activity duration that typically began at 3pm and lasts until midnight. The total number of trips for this RAP equaled 3.3 (lowest of all RAPs). The work activity's average distance from home is 7 miles.

4.4.2. Adults Not Employed Full-Time

A similar process to the one used to identify the groups for Full-time Working Adults was used to identify groups for the Adults Not Employed Full-time subset. A four-group RAP set was selected for analysis from the clustering process that started with two groups and ended at seven groups. Note that while some of the groups are name in a similar fashion to the groups identified for Adults Employed Full-time, the specifics of the RAPs are different for this data subset. Again, a No Travel RAP was present in the data but not a part of the classification procedure. For the adults not employed full-time subset, the RAP set selected for further analysis was combined from an original six group case into the following four RAPs:

B1. Work/School: A 6 hour workday or school day between 8am - 5pm

B2. Maintenance: Several noontime maintenance activities lasting a few hours

B3. Discretionary: Several noontime discretionary activities lasting a few hours

B4. Various Short Activities: Mostly stayed home; some nearby activities for short times

The RAP rules developed from the classification are the following:

1. If the largest duration out-of-home activity is maintenance and the maintenance duration is greater than 2 hours, then the pattern is classified as Maintenance.
2. If the largest duration out-of-home activity is discretionary and discretionary duration is greater than 2 hours, then the pattern is classified as Discretionary.
3. If the largest duration out-of-home activity is work or school and the activity is greater than 2 hours, then the pattern is classified as Work/School.
4. Else, the pattern is classified as a Various Short Activities.

5. If no out-of-home activities, then pattern is classified as a No Travel.

Figures 4.6 to 4.9 provide a more detailed look at the activity profiles for all the RAPs in the data subset that give rise to the above RAP descriptions and rules. **Tables 4.5 to 4.8** present the socioeconomic, activity, and travel statistics of each of the four RAPs. The average individual is a little more than 50, likely female (62%), and has a driver's license (90%). The households lifecycles of the individuals are primarily "Couples without Children" (35%), followed by "Unrelated Persons" (21%), "Single Person Households" (20%), and "Single Worker Couples

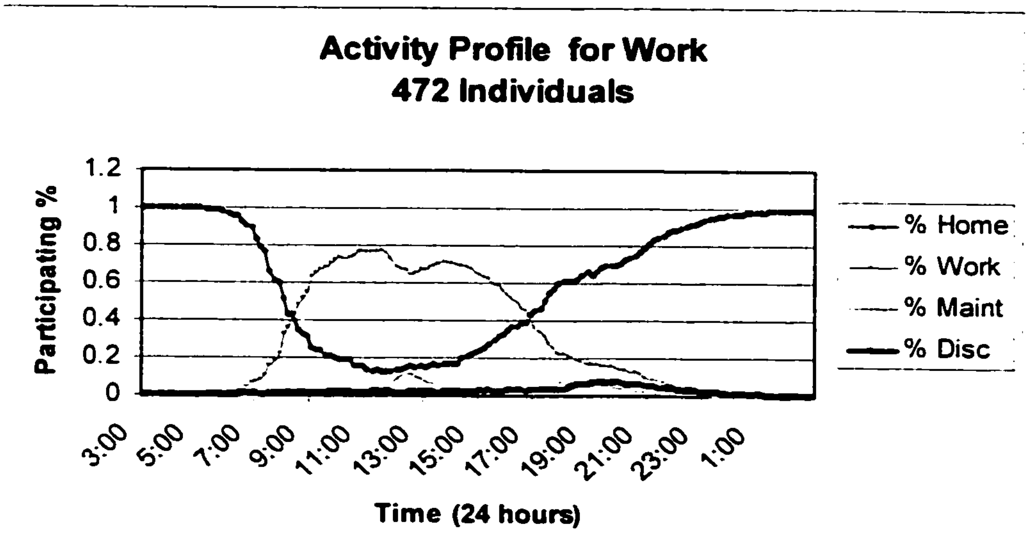

Figure 4.6 Adults Not Employed Full-time: Activity Profile for Work RAP

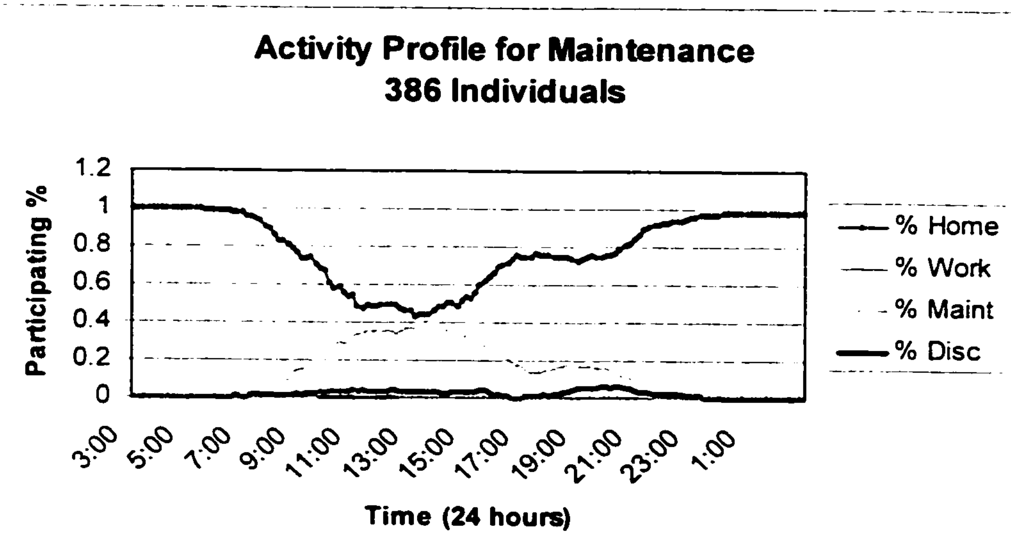

Figure 4.7 Adults Not Employed Full-time: Activity Profile for Maintenance RAP

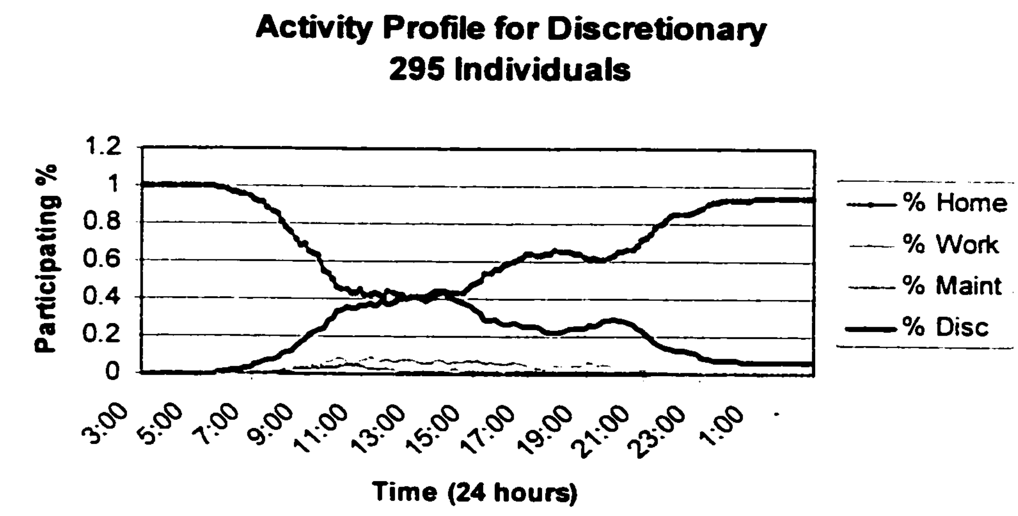

Figure 4.8 Adults Not Employed Full-time: Activity Profile for Discretionary RAP

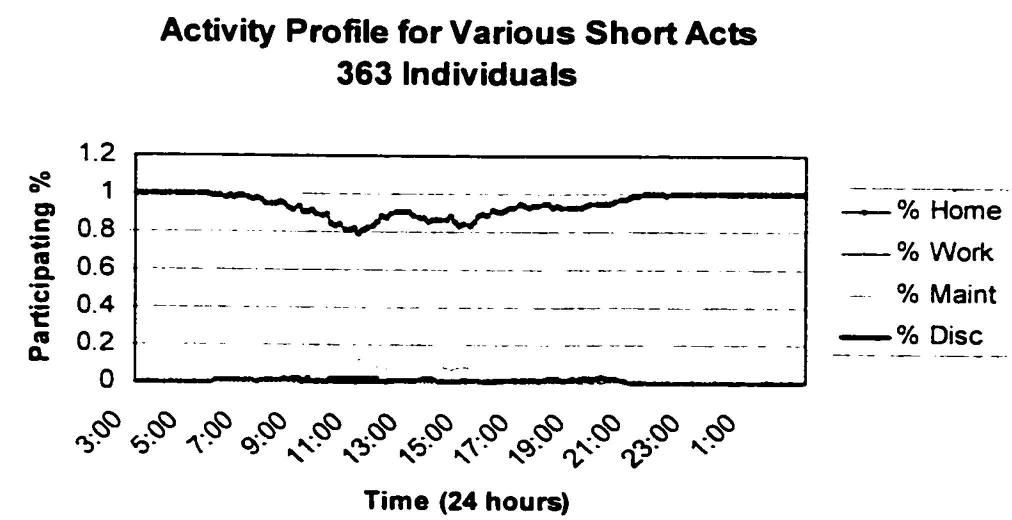

Figure 4.9 Adults Not Employed Full-time: Activity Profile for Various Short Acts RAP

Table 4.5a Descriptive Statistics for Adults Not Employed Full-time by RAP

Variable/ Group	Size		Sex			License			Homeownership		
	Freq.	Prop.		Freq.	Prop.		Freq.	Prop		Freq.	Prop.
Work/School	472	31%	Female	257	54%	No	40	9%	Own	334	71%
			Male	215	46%	Yes	431	91%	Rent	136	29%
Maintenance	386	26%	Female	258	67%	No	45	12%	Own	305	79%
			Male	128	33%	Yes	340	88%	Rent	80	21%
Discretionary	295	20%	Female	180	61%	No	28	10%	Own	229	78%
			Male	115	39%	Yes	265	90%	Rent	64	22%
Various Short Acts	363	24%	Female	245	68%	No	38	11%	Own	306	84%
			Male	118	33%	Yes	325	89%	Rent	57	16%
All RAPs	1516	100%	Female	940	62%	No	151	10%	Own	1174	77%
			Male	576	38%	Yes	1361	90%	Rent	337	22%

* "Don't Know/Refused" replies not included in table.

Table 4.5b Descriptive Statistics for Adults Not Employed Full-time by RAP

Variable/ Group	Median Income&	Mean Hh. Size (Sdev)&	Mean Hh. Vehicles (Sdev)&	Mean Age (Sdev)&
Work/School	$40K-$45K	2.8 (1.3)	2.0 (1.0)	40 (17)
Maintenance	$35K-$40K	2.3 (1.1)	1.7 (0.9)	57 (18)
Discretionary	$35K-$40K	2.4 (1.3)	1.9 (1.1)	54 (20)
Various Short Acts	$35K-$40K	2.6 (1.4)	1.9 (1.0)	56 (18)
All RAPs	$35K-$40K	2.5 (1.2)	1.9 (1.0)	51 (20)

Table 4.6 Lifecycle for Adults Not Employed Full-time by RAP : Frequency and Proportion

Group/ Lifecycle	Work/School		Maint.		Disc.		VSA		All RAPs	
	Freq.	Prop.	Freq.	Prop.	Freq.	Prop.	Freq.	Prop.	Freq	Prop.
Single Person	72	15%	89	23%	69	23%	66	18%	296	20%
Single Parent	21	4%	7	2%	6	2%	6	2%	40	3%
Couple w/o Child	119	25%	161	42%	107	36%	139	38%	526	35%
Single Worker Couple w/ Children	89	19%	55	14%	49	16%	69	19%	262	17%
Dual Worker Couple w/ Children	36	8%	8	2%	8	3%	20	6%	72	5%
Unrelated Persons	135	29%	66	17%	56	19%	63	17%	320	21%
All Lifecycles	366	100%	386	100%	295	100%	822	100%	1516	100%

Table 4.7 Activity Statistics for Adults Not Employed Full-time by RAP Group: Mean (Stdev)

Group/ Variable	Work/ School	Maint.	Disc.	VSA	All RAPs
Number Acts	5.3 (2.1)	6.0 (2.6)	5.7 (2.3)	4.1 (1.7)	5.2 (2.3)
Home Acts	2.5 (0.7)	2.7 (0.9)	2.7 (1.0)	2.4 (0.7)	2.6 (0.8)
Work Acts	1.1 (1.0)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.4 (0.7)
Shop Gen. Acts	0.3 (0.5)	1.2 (1.1)	0.5 (0.8)	0.7 (0.7)	0.7 (0.9)
Shop Oth. Acts	0.0 (0.0)	0.0 (0.3)	0.0 (0.1)	0.0 (0.1)	0.0 (0.2)
PB Acts	0.1 (0.5)	0.8 (0.9)	0.2 (0.6)	0.3 (0.7)	0.4 (0.7)
Soc/Rec. Acts	0.3 (0.5)	0.4 (0.6)	1.7 (0.9)	0.2 (0.4)	0.6 (0.8)
Dine Out Acts	0.3 (0.5)	0.5 (0.6)	0.2 (0.5)	0.1 (0.3)	0.3 (0.5)
School Acts	0.4 (0.6)	0.0 (0.1)	0.1 (0.2)	0.0 (0.2)	0.1 (0.4)
Serve Acts	0.2 (0.7)	0.3 (0.8)	0.2 (0.7)	0.3 (0.7)	0.3 (0.7)
Chgtrvl. Acts	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Home Dur.	14.6 (2.8)	18.7 (2.7)	17.1 (3.4)	22.3 (0.9)	18.0 (3.9)
Work Dur.	5.1 (3.7)	0.0 (0.2)	0.1 (0.5)	0.0 (0.2)	1.6 (3.1)
ShopGen.Dur.	0.2 (0.5)	1.3 (1.3)	0.3 (0.5)	0.5 (0.5)	0.5 (0.9)
ShopOth.Dur.	0.0 (0.0)	0.1 (0.3)	0.0 (0.0)	0.0 (0.1)	0.0 (0.2)
Per. Bus. Dur.	0.1 (0.4)	1.1 (2.0)	0.1 (0.4)	0.2 (0.3)	0.4 (1.1)
Soc/Rec Dur.	0.5 (1.0)	0.5 (0.9)	4.6 (3.0)	0.2 (0.5)	1.2 (2.1)
Dine Out Dur.	0.3 (0.7)	0.8 (1.4)	0.3 (0.6)	0.1 (0.3)	0.4 (0.9)
School Dur.	2.0 (3.0)	0.0 (0.2)	0.1 (0.6)	0.0 (0.1)	0.6 (1.8)
Serve Dur.	0.0 (0.2)	0.1 (0.5)	0.0 (0.1)	0.0 (0.1)	0.1 (0.3)
ChgTrvl Dur.	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Travel Dur.	1.3 (0.8)	1.4 (0.8)	1.5 (0.9)	0.7 (0.5)	1.2 (0.8)

Table 4.8 Travel Statistics for Adults Not Employed Full-time by RAPs: Mean (Stdev)

Group/ Variable	Work/ School	Maint.	Disc.	VSA	All RAPs
Number Trips	4.1 (2.1)	4.9 (2.6)	4.6 (2.3)	3.0 (1.7)	4.1 (2.2)
HBW Trips	1.3 (1.1)	0.1 (0.4)	0.1 (0.5)	0.2 (0.5)	0.5 (0.9)
HBO Trips	1.1 (1.3)	3.4 (1.8)	3.3 (1.7)	2.4 (1.4)	2.4 (1.8)
NHBNW Trips	0.4 (0.9)	1.4 (1.6)	1.1 (1.4)	0.4 (0.8)	0.8 (1.3)
NHBW Trips	0.6 (1.2)	0.0 (0.2)	0.1 (0.2)	0.0 (0.1)	0.2 (0.7)
HBS Trips	0.6 (1.0)	0.1 (0.3)	0.1 (0.4)	0.1 (0.4)	0.2 (0.7)
HBC Trips	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Vehicle Trips	3.3 (2.3)	4.3 (2.8)	4.0 (2.4)	2.6 (1.8)	3.5 (2.4)
Transit Trips	0.3 (0.8)	0.1 (0.6)	0.1 (0.5)	0.0 (0.2)	0.2 (0.6)
Ped. Trips	0.5 (1.1)	0.4 (1.0)	0.5 (1.3)	0.4 (1.0)	0.4 (1.1)
Work/School/Scl. Trips	1.4 (0.8)	0.1 (0.2)	0.1 (0.3)	0.1 (0.2)	0.5 (0.8)
Maint. Trips	0.9 (1.3)	2.7 (1.7)	1.2 (1.3)	1.4 (1.0)	1.5 (1.5)
Disc. Trips	0.3 (0.5)	0.4 (0.6)	1.6 (0.8)	0.2 (0.4)	0.5 (0.8)
Home Trips	1.5 (0.7)	1.7 (0.9)	1.7 (1.0)	1.4 (0.7)	1.6 (0.8)
AM Peak Trips	0.8 (0.8)	0.4 (0.7)	0.5 (0.8)	0.3 (0.7)	0.5 (0.8)
MIDDAY Trips	1.6 (1.5)	3.0 (1.9)	2.5 (1.8)	2.0 (1.6)	2.3 (1.8)
PM Peak Trips	1.0 (0.9)	0.8 (1.0)	0.8 (0.9)	0.5 (0.9)	0.8 (0.9)
Off Peak Trips	0.7 (0.8)	0.6 (0.9)	0.7 (0.9)	0.2 (0.6)	0.6 (0.8)

with Children" (17%). The households have an average household size of 2-½ (mostly single and double person). The households tend to own their homes (77%). are primarily lower income ($35K – $40K). though a fair amount of middle and higher income groups exist. Keep in mind that the statistics reported are individual-based household statistics and that the Adults Not Employed Full-time statistics may overlap with Adults Employed Full-time and therefore should be analyzed with caution.

The Work/School RAP (**B1**) consisted of 31 percent of the patterns in the data segment. Almost an equal proportion of females to males (54%. much lower than the combined RAPs). and by far the youngest (40 vs. 51 years of age). Households in this RAP have the highest median income of all RAPs ($40K – $45K) as well as the largest household size. There is a larger than expected presence of the "Unrelated Persons" and "Dual Worker Couples with Children" lifecycle groups and a smaller than expected presence of "Couples w/o Children" when compared to all of the RAP member households. Most members executed a work pattern that included a 6-hour workday. This is three hours less than the Standard Work pattern that Full-time Adult Workers typically execute. A large number of members executed a school pattern as well. The data seems to indicate that around 11 percent of the RAP members exhibited some midday maintenance activity (lunchtime dining). The work or school activity's average distance from home is 6 miles.

The Maintenance RAP (**B2**) consists of 26 percent of all activity-travel patterns. 67 percent of the individuals in this RAP are female and average 57 years of age. Households makeup is different than the overall RAPs in that more "Couples without Children" and "Single Person" lifecycle groups are present at the expense of "Single and Dual Worker Couples with Children". In addition, the average household size is lower than the combined RAPs (2.3 vs. 2.5) and the median incomes are between $25K – $30K. The typical day is spent in and out of home with a number of maintenance activities centering around noon that cumulatively last more than 4 hours resulting in an average of 4.9 trips per day. The typical activities consist of those classified as shopping, personal business, and dining out in diminishing frequency. The activities' average distances from home average 5-½ miles.

The Discretionary RAP (**B3**) consists of 20 percent of all activity-travel patterns. The individuals are mostly female (61%, similar to all RAPs) and average in the mid-50's (54). Household makeup is very similar to the combined RAPs, though lifecycle membership is somewhat more related to the Maintenance RAP. Specifically, "Couples without Children" is the largest lifecycle group, though a larger proportion of the "Single Person" lifecycle group is present at the expense of both "Single and Dual Worker Couples with Children". Interestingly, while some differences exist in the demographic makeup of the Maintenance and Discretionary RAPs, the differences between the two are very minor. The typical day consists of one or more long out-of-home discretionary activity (5-½ hours), typically beginning late morning and ending in the afternoon with an average of 9 miles from home with discretionary activities composing most of the out of home time. A smaller fraction of individuals also participate in discretionary activities in the evening as well, around than 20 percent of the RAP members.

The Various Short Activities RAP (**B4**) consists of 24 percent of all activity-travel patterns and both the individuals and households that make up the RAP. Differences exist between the RAP and the overall subset socio-economic characteristics, particularly the home ownership rates (84% vs. 77%), large proportion of females (68% vs. 62%), and relatively small number of "Unrelated Persons" lifecycle group. The typical pattern has on average much lower activity participation (4.1 activities vs. 5.2 activities overall) and trips (3.0 vs. 4.1). Moreover, even the out-of-home activities in which each individual participate in have very small durations and by definition none have a total duration more than two hours. Specifically, the pattern executed typically engages in a few different activities throughout the day with a short duration and very near home (around 1 mile from home).

4.4.3. Children

Children made up the last category for classification. The classification was similar to the earlier clustering and started with two groups and ended at eight groups. The RAP set selected for further analysis was determined based on the size of the groupings and a subjective analysis of their makeup. RAPs with equivalent activity-profiles and only small differences in distance were combined to avoid over defining the RAPs. A final five-group RAP set was selected for further analysis. Note that a sixth RAP, No Travel, was present in the data but not part of the classification procedure.

C1. Standard School: A 6 hour school day between 8am - 5pm

C2. Power School: An 8 hour school day between 8am - 5pm

C3. Maintenance: "tag-along" with an adult parent executing a Maintenance RAP (**B2**)

C4. Discretionary: "tag-along" with an adult parent executing a Discretionary RAP (**B3**)

C5. Various Short Activities: "tag-along" with an adult parent a VSA RAP (**A5** or **B4**)

The rules developed from the results follow based on the largest duration activity.

1. If the largest duration out-of-home activity is school, with duration between 2 and 9 hours , then the pattern is classified as a Standard School.

2. If the largest duration out-of-home activity is school with duration greater than 9 hours, then the pattern is classified as a Power School.
3. If the largest duration out-of-home activity is maintenance, and the maintenance duration is greater than 2 hours, then the pattern is classified as Maintenance.
4. If the largest duration out-of-home activity is discretionary and the discretionary duration is greater than 2 hours, then the pattern is classified as a Discretionary.
5. Else, the pattern is classified as Various Short Activities.
6. If no out-of-home activities, then the pattern is classified as a No Travel.

Tables 4.9 to 4.12 present the socioeconomic, activity, and travel statistics of each of the four RAPs. **Figures 4.10 to 4.14** show the activity profile of the RAPs that make up this category.

The average individual is 9 years, evenly split between female and male (51% to 49%), and does not have a driver's license (94%). The households lifecycles of the individuals are primarily "Single Worker Couple with Children" (46%), followed by "Dual Worker Couple with Children" (32%), "Single Parent" (14%), and "Unrelated Persons" (8%). The households have an average

Table 4.9a Descriptive Statistics for all Children by RAP

Variable/ Group	Size		Sex			License			Homeownership		
	Freq.	%		Freq.	%		Freq.	%		Freq.	%
Standard School	637	60%	Female	311	49%	No	597	94%	Own	526	83%
			Male	326	51%	Yes	37	6%	Rent	110	17%
Power School	62	6%	Female	36	58%	No	52	84%	Own	48	77%
			Male	26	42%	Yes	10	16%	Rent	12	19%
Maintenance	87	8%	Female	44	51%	No	85	98%	Own	72	74%
			Male	43	49%	Yes	2	2%	Rent	15	26%
Discretionary	156	15%	Female	85	55%	No	149	96%	Own	115	74%
			Male	71	46%	Yes	7	4%	Rent	41	26%
Various Short Acts	119	12%	Female	63	53%	No	118	99%	Own	94	79%
			Male	56	47%	Yes	1	1%	Rent	24	20%
All Groups	1061	100%	Female	539	51%	No	1001	94%	Own	855	81%
			Male	522	49%	Yes	57	5%	Rent	202	19%

* "Don't Know/Refused" replies not included in table.

Table 4.9b Descriptive Statistics for all Children by RAP

Variable/ Group	Median Income	Mean Hh. Size (Sdev)	Mean Hh. Vehicles (Sdev)	Mean Age (Sdev)
Standard School	$45K – $50K	4.3 (1.4)	2.1 (0.9)	11 (3.7)
Power School	$50K – $55K	3.8 (1.1)	2.2 (1.2)	9 (6.0)
Maintenance	$50K – $55K	3.7 (0.9)	1.9 (0.8)	5 (4.6)
Discretionary	$35K – $40K	4.1 (1.1)	2.2 (0.9)	7 (5.2)
Various Short Acts	$35K – $40K	4.5 (1.2)	2.0 (0.8)	5 (3.8)
All Groups	$45K – $50K	4.2 (1.3)	2.1 (0.9)	9 (4.8)

* "Don't Know/Refused" replies not included in table.

Table 4.10a Lifecycle for all Children by RAP: Frequency and Proportion

Group/ Lifecycle	Standard School		Power School		Maintenance	
	Freq.	Prop.	Freq.	Prop.	Freq.	Prop.
Single Person	2	0%	0	0%	0	0%
Single Parent	84	13%	12	19%	11	13%
Couple w/o Child	3	0%	2	3%	1	1%
Single Worker Couple w/ Children	269	42%	17	27%	46	53%
Dual Worker Couple w/ Children	230	36%	29	47%	19	22%
Unrelated Persons	49	8%	2	3%	10	12%
All Lifecycles	637	100%	62	100%	87	100%

Table 4.10b Lifecycle for all Children by RAP: Frequency and Proportion

Group/ Lifecycle	Discretionary		VSA		All RAPs	
	Freq.	Prop.	Freq.	Prop.	Freq.	Prop.
Single Person	1	1%	1	1%	4	0%
Single Parent	26	17%	11	9%	144	14%
Couple w/o Child	0	0%	1	1%	7	1%
Single Worker Couple w/ Children	80	51%	71	60%	483	46%
Dual Worker Couple w/ Children	36	23%	26	22%	340	32%
Unrelated Persons	13	8%	9	8%	83	8%
All Lifecycles	156	100%	119	100%	1061	100%

Table 4.11 Activity Statistics for all Children by RAP

Group/ Variable	Standard School	Power School	Maint.	Disc.	VSA	All RAPs
Number Acts	4.3 (1.7)	4.7 (1.4)	5.0 (2.0)	5.4 (2.1)	4.4 (1.6)	4.6 (1.8)
Home Acts	2.3 (0.6)	2.3 (0.6)	2.3 (0.6)	2.6 (0.7)	2.5 (0.7)	2.4 (0.6)
Work Acts	0.0 (0.2)	0.2 (0.5)	0.0 (0.2)	0.0 (0.0)	0.0 (0.0)	0.0 (0.2)
Shop Gn. Acts	0.1 (0.3)	0.0 (0.0)	1.1 (1.3)	0.3 (0.5)	0.5 (0.7)	0.3 (0.6)
Shop Ot. Acts	0.0 (0.0)	0.0 (0.0)	0.0 (0.2)	0.0 (0.0)	0.0 (0.1)	0.0 (0.0)
PB Acts	0.1 (0.3)	0.1 (0.4)	0.5 (0.6)	0.1 (0.2)	0.1 (0.4)	0.1 (0.4)
Soc/Rec. Acts	0.4 (0.6)	0.2 (0.4)	0.3 (0.7)	1.9 (1.0)	0.9 (1.0)	0.7 (0.9)
Dine Out Acts	0.2 (0.4)	0.3 (0.5)	0.4 (0.6)	0.3 (0.5)	0.1 (0.3)	0.2 (0.5)
School Acts	1.2 (0.5)	1.5 (0.8)	0.0 (0.2)	0.2 (0.6)	0.0 (0.2)	0.8 (0.7)
Serve Acts	0.1 (0.4)	0.1 (0.3)	0.3 (0.7)	0.1 (0.2)	0.3 (0.6)	0.1 (0.5)
Chgtrvl. Acts	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Home Dur.	15.7 (2.0)	12.4 (2.3)	18.0 (2.8)	16.2 (3.8)	20.4 (2.3)	16.4 (3.3)
Work Dur.	0.1 (0.8)	1.2 (2.6)	0.0 (0.3)	0.0 (0.3)	0.1 (0.7)	0.1 (0.9)
ShopGen.Dur.	0.1 (0.3)	0.0 (0.1)	1.3 (1.8)	0.2 (0.5)	0.5 (1.0)	0.2 (0.7)
ShopOth.Dur.	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Per. Bus. Dur.	0.1 (0.3)	0.1 (0.2)	1.8 (3.0)	0.0 (0.2)	0.1 (0.5)	0.2 (1.0)
Soc/Rec Dur.	0.7 (1.2)	0.4 (0.7)	0.3 (0.6)	5.5 (2.9)	1.4 (1.8)	1.3 (2.3)
Dine Out Dur.	0.2 (0.4)	0.2 (0.4)	1.0 (2.0)	0.2 (0.7)	0.1 (0.5)	0.2 (0.7)
School Dur.	6.2 (1.4)	9.0 (2.8)	0.1 (0.6)	0.5 (1.4)	0.3 (0.9)	4.3 (3.3)
Serve Dur.	0.0 (0.0)	0.0 (0.1)	0.2 (1.2)	0.0 (0.00	0.0 (0.1)	0.0 (0.3)
ChgTrvl Dur.	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Travel Dur.	0.9 (0.5)	1.0 (0.6)	1.0 (0.6)	1.2 (0.7)	0.9 (0.6)	0.9 (0.6)

Table 4.12 Travel Statistics for all Children by RAP

Group/ Variable	Standard School	Power School	Maint	Disc	VSA	All RAPs
Number Trips	3.1 (1.4)	3.4 (1.3)	3.9 (2.0)	4.0 (1.9)	3.3 (1.6)	3.3 (1.6)
HBW Trips	0.0 (0.2)	0.3 (0.7)	0.0 (0.2)	0.0 (0.1)	0.0 (0.2)	0.0 (0.2)
HBO Trips	0.8 (1.0)	0.5 (0.7)	2.4 (1.2)	3.0 (1.5)	2.7 (1.3)	1.4 (1.5)
NHBNW Trips	0.4 (0.8)	0.6 (0.9)	1.3 (1.4)	0.7 (1.2)	0.5 (0.9)	0.6 (1.0)
NHBW Trips	0.0 (0.2)	0.1 (0.3)	0.0 (0.1)	0.0 (0.0)	0.0 (0.0)	0.0 (0.1)
HBS Trips	1.8 (0.7)	1.8 (0.9)	0.1 (0.3)	0.2 (0.7)	0.2 (0.4)	1.3 (1.0)
HBC Trips	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Vehicle Trips	1.6 (1.6)	2.8 (1.6)	3.4 (2.3)	3.2 (2.0)	3.0 (1.5)	2.2 (1.9)
Transit Trips	0.8 (1.0)	0.3 (0.5)	0.2 (0.5)	0.2 (0.6)	0.1 (0.4)	0.6 (0.9)
Ped. Trips	0.6 (1.1)	0.4 (1.0)	0.3 (0.8)	0.6 (1.2)	0.3 (0.9)	0.5 (1.0)
Work/Scl.	1.1 (0.3)	1.5 (0.6)	0.0 (0.3)	0.2 (0.3)	0.1 (0.2)	0.8 (0.6)
Trips	0.3 (0.7)	0.4 (0.8)	2.3 (1.3)	0.6 (0.8)	1.0 (1.0)	0.6 (0.9)
Maint. Trips	0.4 (0.6)	0.2 (0.4)	0.3 (0.8)	1.7 (0.9)	0.8 (0.9)	0.6 (0.9)
Disc. Trips	1.3 (0.6)	1.3 (0.6)	1.3 (0.6)	1.6 (0.8)	1.5 (0.7)	1.4 (0.6)
Home Trips						
AM Pk Trips	0.9 (0.4)	0.9 (0.5)	0.4 (0.7)	0.3 (0.5)	0.4 (0.7)	0.7 (0.6)
MD Trips	1.2 (0.8)	0.6 (0.9)	2.4 (1.7)	1.8 (1.5)	1.8(1.6)	1.4 (0.2)
PM Pk Trips	0.5 (0.8)	1.1 (0.7)	0.7 (0.8)	1.0 (0.8)	0.8 (0.9)	0.7 (0.9)
OffPk Trips	0.3 (0.6)	0.8 (0.8)	0.4 (0.7)	0.8 (0.9)	0.4 (0.8)	0.4 (0.7)

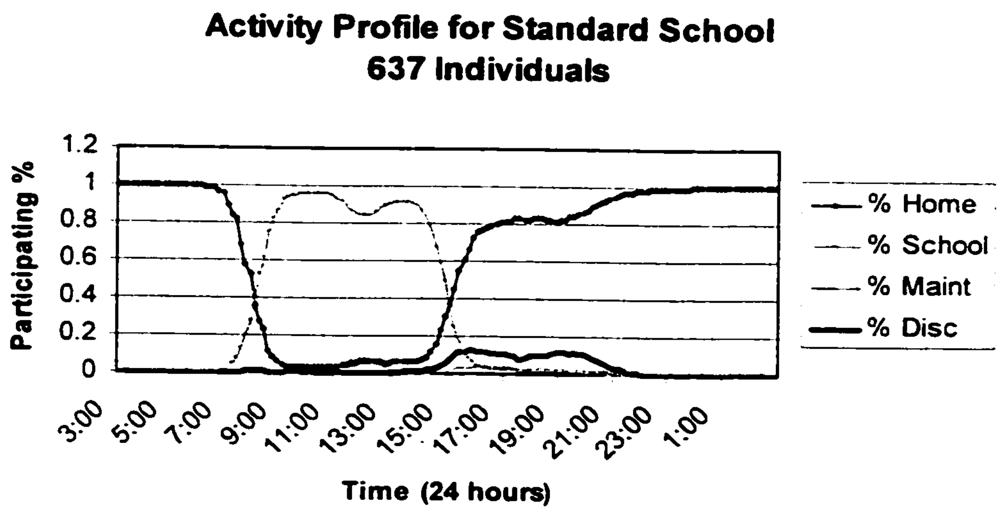

Figure 4.10 Children: Activity Profile for Standard School

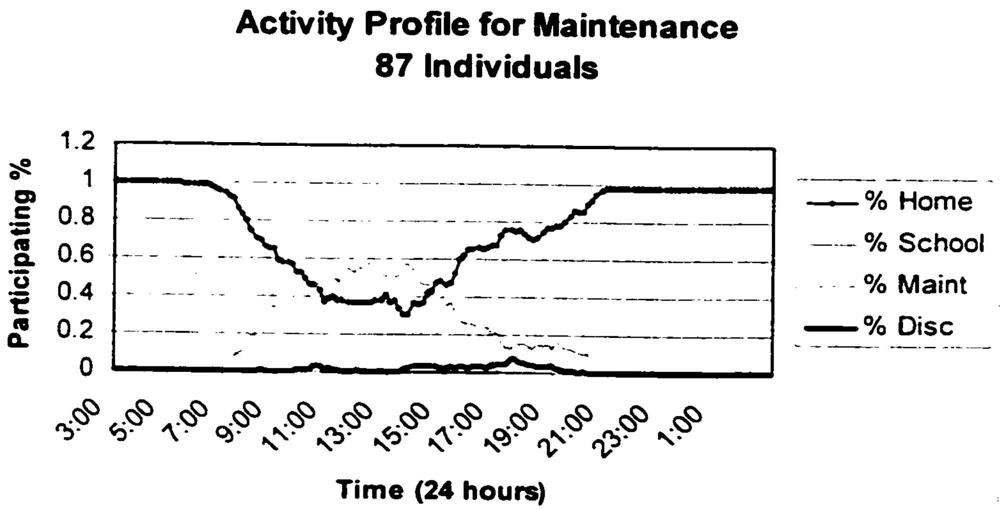

Figure 4.11 Children: Activity Profile for Maintenance

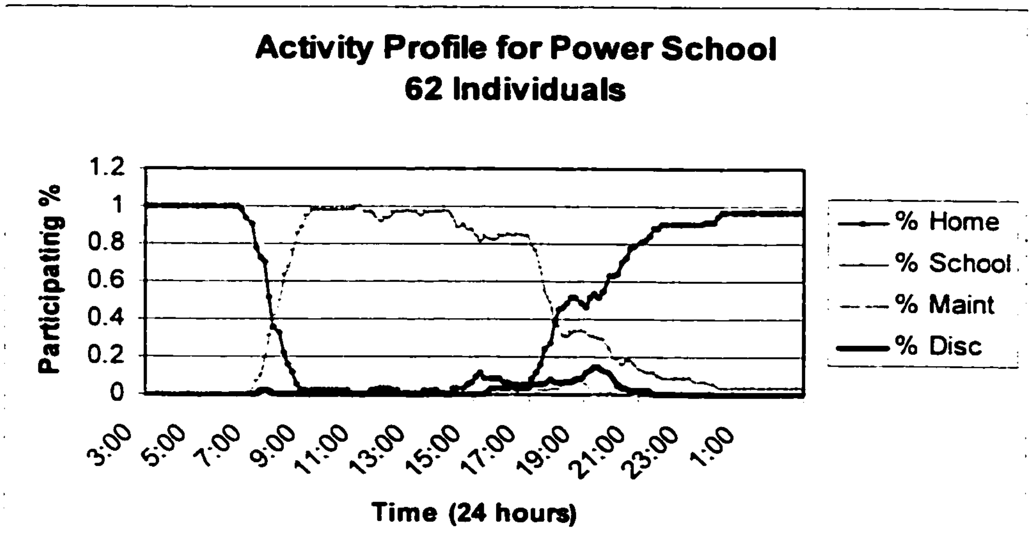

Figure 4.12 Children: Activity Profile for Power School

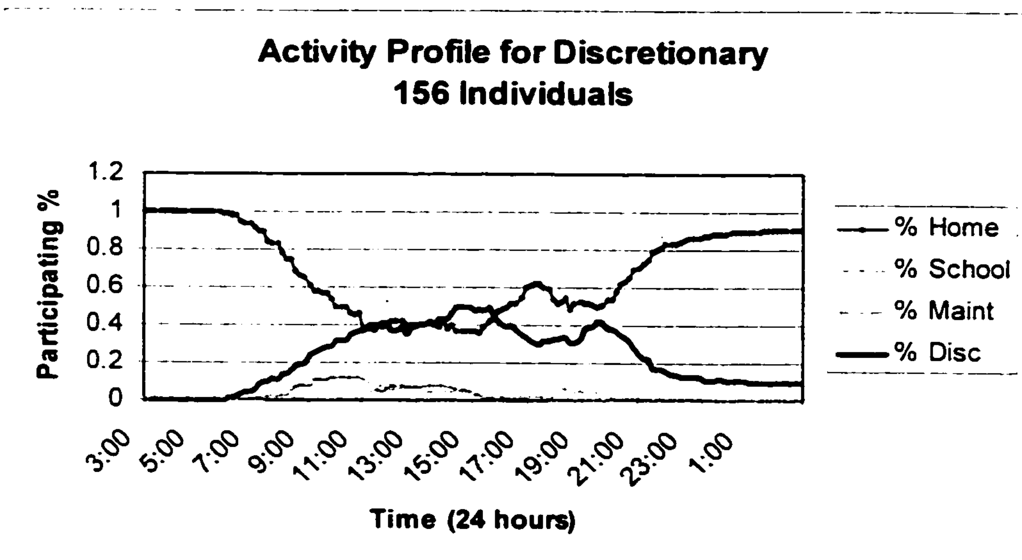

Figure 4.13 Children: Activity Profile for Discretionary

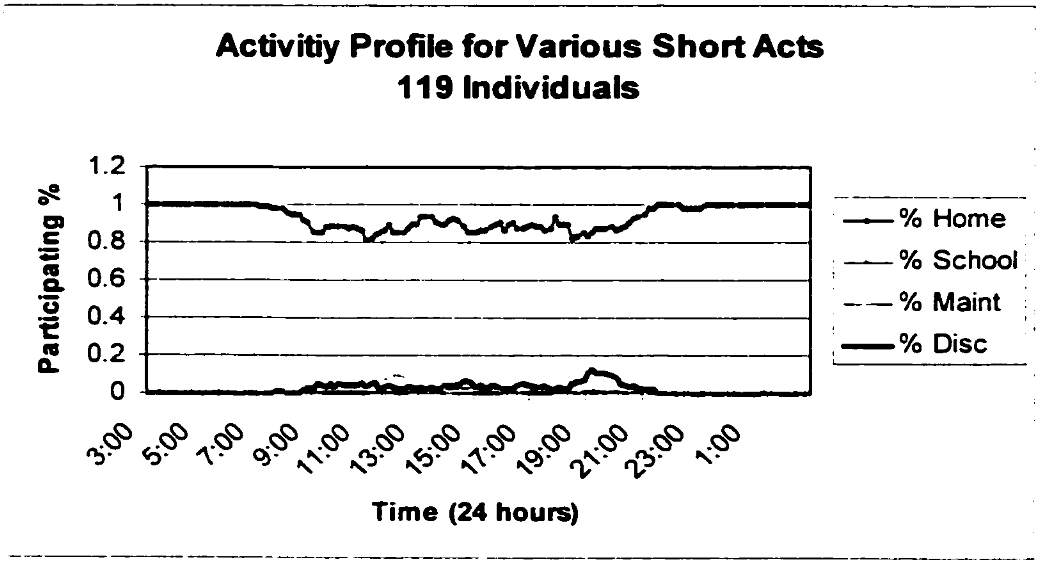

Figure 4.14 Children: Activity Profile for Various Short Acts

household size of 4.2. The households tend to own their homes (81%), are primarily middle income ($45K – $50K).

The Standard School RAP (**C1**) consisted of the majority of Children's activity-travel patterns (60%). Socioeconomically, this RAP is on average older (11 vs. 9 years) and more male (51% vs. 49%) than the overall averages, but is similar to the overall lifecycle, household size, and income statistics. Most members executed an average 6 hour school activity usually between 8 am and 3 pm without a midday maintenance activity. The school activity's average distance from home is 2 miles. Around 12 percent of the RAP went out on a discretionary activity at around 7 pm.

The Power School RAP (**C2**) consisted of 6 percent of the activity-travel patterns. The Power School RAP is interesting in that households are made up of the highest proportion of "Dual Worker Couples with Children" (47% versus 32%) and higher income households ($50K - $55K) than in the overall population. Mean age is 9, though there is a wide discrepancy in ages as the distribution of ages is bimodal (both young and older children, with peaks at 4 years and 16 years) and proportionally more females than males (58% versus 42%). It is likely that this group includes two types of children: children can not stay home without a parent who directly go to after school daycare centers and older children who stay after school to participate in after-school activities. The typical school activity is 2 hours longer than the Standard School RAP's school activity at 8-½ hours, somewhere between 8 AM and 4:30 PM. The activity durations indicate that both work (average 1½ hours) and social/recreation (average1 hour) activities are common in this

RAP, mostly during the evening hours. The school's activity's average distance from home is 5 miles.

The Maintenance RAP (C3) consists eight percent of all activity-travel patterns. Children in this RAP tend to be younger (5 years), from households that are smaller than average, and have higher incomes ($50K - $55K). The typical day is does not contain school and is rather similar to an adult's maintenance pattern with a day made up of mostly shopping, personal business, or dining out activities averaging 1, 3½, and 2 hours, respectively. The Maintenance RAP is possibly a "tag-along" RAP with an adult parent where the child is essentially accompanying an adult throughout most of the day. The average distance from home for the different activities ranges from 1½ miles to around 3½ miles.

The Discretionary RAP (C4) makes up the second largest group with 15 percent of all activity-travel patterns. This RAP makeup is similar to the Power School RAP in that it has a bimodal age distribution with both younger children (4 years) and older children (14 years). It has a large proportion of households come from the "Single Parent" lifecycle group (17%) and have lower income households compared to the overall data subset ($35K -$40K). The typical day does not contain a school activity and is rather similar to an adult's discretionary pattern with a day made up of an average of 2 social/recreational activities. The typical daily duration spent in social/recreational activities is 5½ hours somewhere between the hours of 9 am and 6 pm. The average distance from home of these activities is 2 to 6 miles. For the younger aged children in this RAP, this is possibly a "tag-along" RAP with an adult parent.

RAP Various Short Activities (**C5**) makes up the third largest group at 12 percent. This RAP contains the youngest children (mean age of 5 years), a largest proportion of which are from "Single Worker Couples" (60%), have the largest household size, and low incomes ($35K – $40K). The typical day consists of a number of different activities with short durations and close to home. Activity statistics suggest that likely activities include general shopping and social/recreational activities that average ½ and 1 hour, respectively, and are around 1 mile from home.

The identification of the RAPs from the individual activity-travel patterns of subsets of the original data into adults employed full-time, adults not employed full-time, and children proved successful in identifying a small number of distinct patterns. Specifically, when individuals are segmented by employment status and age first, differences between the activity-travel behavior of these pre-defined categories is increased and the differences within each group decreased.

4.5. ACTIVITY-BASED PATTERN GENERATION MODELS

In standard travel demand modeling, the first phase consists of trip generation and aims to estimate the magnitude of travel demand. The nature of the trip ends is used to classify trips as either productions or attractions at a zonal or household (trip rate) level. Common methods used to model trip generation are linear regression and category analysis. The former method is commonly used to calculate measures of trip attractions, relating measures of land use data to trip attractions; the later more commonly used to associate productions to demographic data. The cross-classification techniques are commonly used in estimating trip productions by creating relatively homogeneous household or person groups based on socio-economic characteristics and then link each group to a set of trip rates from observed data. The production and attraction ends of each trip are then aggregated ; the basic unit of analysis, the trip, does not again exist as an interconnected entity until the second phase of the standard forecasting process, trip distribution. As a result, the models currently used fail to include the spatial and temporal inter-connectivity inherent in household travel behavior.

A pattern generation model serves as a bridge in the difficult transition from trip-based to activity-based models. Pattern generation models have been presented in the past as similar in both construction and application to common trip production models by incorporating a familiar cross-classification structure. They are not by any means limited to such constructs. Rather, they are presented as such to demonstrate their ease of adoption to current modeling frameworks as they do not need the modeler to acquire additional skill sets and can functionally replace a calibrated trip generation model with very little disruption in the current multi-step travel demand process. The only application-level difference between conventional trip generation models and pattern generation models is that the model does not simply assign a pattern each individual *per se*, but a likelihood that an individual may engage in a pattern from a set of patterns is assigned. A specific pattern and its associated average trips can then be randomly assigned to the individual based on the assigned possibility, effectively reducing the pattern model to a conventional trip generation model. By nature, the pattern model includes much more information about the activity and travel behavior of the individual under consideration, including the time of day, the activity type associated with each trip, the chaining behavior, and other characteristics. These attributes can be used in the later stages of the travel forecasting methodology by the modeler.

As constructed, the sample pattern generation models developed here are cross-classification models that can take a number of parameters. The first model constructed takes as its parameters *employment status* (full-time or non full-time) and *average age group* (adult or child) of the individual under consideration while the second takes *employment status* and number of *household vehicles.* Once classified into a category based on the independent variables of the individual in question, the likelihood that the individual will participate in each pattern can be assigned to the individual, where the identified patterns are equivalent to the RAPs. The assignment can be done in a number of distinct ways, though the most intuitive is to randomly select a RAP for each individual using a Monte Carlo approach based on the probabilities allocated to the individual in the previous step. The RAPs can be reduced into trip productions based on the average number of trips produced by individuals from that RAP if required. The advantage of this approach is that a number of new variables are now assigned to each individual in addition to trips, notably activity and location attributes that previously were not part of trip generation models. These can then be applied to subsequent models in the four-step approach, including trip distribution and mode choice models to increase their accuracy

Tables 4.13 and 4.14 present the two pattern generation models for all adults. Both pattern generation models are set up as category tables that specify the likelihood that an individual will participate in a set of possible RAPs. Also provided for each cell are standard trip generation rates (though these rates are skewed upward since individuals without travel were not included in the analysis). The first model segments individuals by age, employment status, and lifecycle and assigns a likelihood that an individual participates in one of the defined RAPs. Using the data in **Table 4.13**, consider an individual that fits into the category of employed adult in a Single Parent Household. A conventional trip generation model using the same classification format would estimate 4.1 trips per day for the individual in the category. Rather than assigning 4.1 trips to the individual, the activity-based model estimates a 35 percent probability that the individual will participate in a Standard Work-like pattern. The probability of the individual executing a RAP

Table 4.13 An Activity-based Pattern Generation Model for Adults Segmented by Employment Status and Lifecycle Group

Employment Status / Lifecycle Group	Adults Employed Full-time	Adults Not Employed Full-time	Children
1: Single Person Household Trips: mean (stdev)	Standard Work: 30% Power Work: 6% Late Work: 5% Work-Maintenance: 45% Various Short Acts: 13% *Trips/adult: 4.1 (2.2)*	Work/School: 24% Maintenance: 30% Discretionary: 23% Various Short Acts: 22% *Trips/adult: 4.1 (2.4)*	
2: Single Parent Household (children under 18) Trips: mean (stdev)	Standard Work: 35% Power Work: 13% Late Work: 6% Work-Maintenance: 36% Various Short Acts: 11% *Trips/adult: 4.0 (2.0)*	Work/School: 53% Maintenance: 18% Discretionary: 15% Various Short Acts: 15% *Trips/adult: 4.5 (2.2)*	School/Work: 18% Power School/Work: 8% Maintenance: 8% Discretionary: 58% Various Short Acts: 8% *Trips child:3.5 (1.8)*
3: Couples* w/o Children Trips: mean (stdev)	Standard Work: 33% Power Work: 9% Late Work: 3% Work-Maintenance: 41% Various Short Acts: 15% *Trips adult: 3.8 (2.0)*	Work/School: 23% Maintenance: 31% Discretionary: 20% Various Short Acts: 26% *Trips/adult: 3.8 (2.0)*	
4: Single Worker Couples* w/ Children Trips: mean (stdev)	Standard Work: 32% Power Work: 13% Late Work: 2% Work-Maintenance: 36% Various Short Acts: 17% *Trips adult: 3.6 (1.8)*	Work/School: 34% Maintenance: 21% Discretionary: 19% Various Short Acts: 26% *Trips/adult: 4.9 (2.6)*	School/Work: 17% Power School/Work: 10% Maintenance: 4% Discretionary: 56% Various Short Acts: 15% *Trips child3.4 (1.6)*
5: Double Worker Couples* w/ Children Trips: mean (stdev)	Standard Work: 36% Power Work: 6% Late Work: 2% Work-Maintenance: 38% Various Short Acts: 19% *Trips adult: 4.1 (2.1)*	Work/School: 50% Maintenance: 11% Discretionary: 11% Various Short Acts: 28% *Trips/adult: 4.2 (2.5)*	School/Work: 11% Power School/Work: 6% Maintenance: 9% Discretionary: 68% Various Short Acts: 8% *Trips childt 3.1 (1.5)*
6: Unrelated Persons Trips: mean (stdev)	Standard Work: 35% Power Work: 9% Late Work: 5% Work-Maintenance: 38% Various Short Acts: 14% *Trips adult: 3.8 (1.9)*	Work/School: 42% Maintenance: 21% Discretionary: 18% Various Short Acts: 20% *Trips/adult: 4.0 (2.2)*	School/Work: 16% Power School/Work: 12% Maintenance: 2% Discretionary: 59% Various Short Acts: 11% *Trips child:3.3 (1.7)*

* Couples includes only Male-Female pairs that are either married or unmarried.

Table 4.14 An Activity-Based Pattern Generation Model for Adults Segmented by Employment Status and Household Vehicles

Employment Status /Vehicles	Adults Employed Full-time	Adults Not Employed Full-time	Children
No Household Vehicles Trips: mean (stdev)	Standard Work: 31% Power Work: 2% Late Work: 13% Work-Maintenance: 29% Various Short Acts: 26% *Trips/adult: 3.4 (1.8)*	Work/School: 32% Maintenance: 26% Discretionary: 17% Various Short Acts: 26% *Trips/adult: 3.5 (1.8)*	School/Work: % Power School/Work: % Maintenance: % Discretionary: % Various Short Acts: % *Trips/child*
One Household Vehicle Trips: mean (stdev)	Standard Work: 31% Power Work: 7% Late Work: 5% Work-Maintenance: 42% Various Short Acts: 15% *Trips/adult: 4.2 (2.2)*	Work/School: 23% Maintenance: 31% Discretionary: 22% Various Short Acts: 24% *Trips/adult: 4.0 (2.3)*	School/Work: % Power School/Work: % Maintenance: % Discretionary: % Various Short Acts: % *Trips/child*
Two Household Vehicles Trips: mean (stdev)	Standard Work: 34% Power Work: 9% Late Work: 3% Work-Maintenance: 40% Various Short Acts: 14% *Trips/adult: 3.8 (1.9)*	Work/School: 32% Maintenance: 25% Discretionary: 18% Various Short Acts: 25% *Trips/adult: 4.2 (2.4)*	School/Work: % Power School/Work: % Maintenance: % Discretionary: % Various Short Acts: % *Trips/child)*
Three or more Household Vehicles Trips: mean (stdev)	Standard Work: 34% Power Work: 8% Late Work: 3% Work-Maintenance: 39% Various Short Acts: 17% *Trips/adult: 3.9 (2.0)*	Work/School: 39% Maintenance: 19% Discretionary: 21% Various Short Acts: 21% *Trips/adult: 4.2 (2.2)*	School/Work: % Power School/Work: % Maintenance: % Discretionary: % Various Short Acts: % *Trips/child*

* Couples includes only Male-Female pairs that are either married or unmarried.

similar to the Power Work, Late Work, Work-Maintenance, and Various Short Activities are 6, 5, 45, and 13 percent. The second model segments individuals by age, employment status, and the number of household vehicles. Using the data in **Table 4.14**, say the same individual who was considered above now fits into the category of employed adult in a one vehicle household. A conventional trip generation model using the same classification format would now estimate 4.2 trips per day for the individual in the category. Rather than assigning 4.2 trips to the individual, the activity-based model estimates a 31 percent probability that the individual will participate in a Standard Work-like pattern. The probability of the individual executing a RAP similar to the Power Work, Late Work, Work-Maintenance, and Various Short Activities are 7, 5, 42, and 15 percent. From these RAPs distributions, the model can randomly select the specific RAP which the individual will participate. This provides a useful alternative than only providing trip rates in a fashion that is just slightly more complex than current trip generation models.

4.5 CONCLUSIONS

The development of the pattern generation model outlined in this chapter uses RAPs as the foundation of the model. A conventional classification approach is used to identify a number of distinct RAPs and to develop rules to easily specify them. Cross-classification techniques are then applied to develop the specific pattern generation models with two examples provided. The approach expounded holds several distinct advantages over conventional trip generation models. First, because the standard model produces trips as its standard output, a number of intermediate models and fixes are applied to address time-of-day and trip purpose. The process can be redefined with the estimation of full activity-travel patterns to be more accurate. Second, these individual patterns provide much more detailed predictions of the movement of individuals within a planning region. which can be converted into mode-specific patterns with the benefit that emissions models can obtain more specific data, including cold and hot starts as elicited from the estimated RAPs. Third. this pattern generation model can be used as a bridge to incorporate the activity-based approach to the current travel demand-modeling framework. That is. the model can reduce.to allow output that is identical to current trip generation models. Fourth. current extensions of this model server as the preliminary module of an activity-based microsimulation model allowing for a full activity-based microsimulation approach to travel demand forecasting.

Such an extension would result in a microsimulation model that uses the activity-pattern generation model as an initial stage is proposed that would redefine the entire travel demand-modeling framework using an activity-based approach. The patterns generated can be converted into a trip origin-destination table and be input directly into mode choice and route choice models. By introducing the proposed pattern generation model alongside conventional trip-based models. the acceptance and understanding of activity-based models will be hastened. The model constructed will also serve as the initial component of an ongoing effort to produce an advanced activity-based microsimulation model aimed at replacing the entire conventional modeling process.

CHAPTER 5

MICROSIMULATION OF DAILY ACTIVITY PATTERNS

5.1 INTRODUCTION

This chapter describes the development of an activity-based microsimulation model for travel demand forecasting 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 -- time-dependent representations 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 were 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 and summarizes the implementation of the generation model. **Section 5.3** demonstrates the construction of the different submodels of the simulations. **Section 5.4** provides a description of the programatic setup: **Section 5.5** summarizes the implementation results: and. **Section 5.6** offers some conclusions and identifies some areas for further research.

5.2 FRAMEWORK FOR AN ACTIVITY-BASED GENERATION MODEL

The foundation for this model is the aggregate classification of individual activity-travel patterns that produced the representative activity patterns (RAPs) from the previous chapter. The key hypotheses in the development of this activity-based microsimulation model are the following:

1. The classification offers a means of associating likelihood that an individual will participate in each RAP
2. The RAPs provide a means of identifying the underlying activity type. location. and duration dimensions for each RAP
3. The distributions can be 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
4. Spatial characteristics can be tied into the simulation via a GIS

These probability distributions are derived from the activity-travel behavior of the individual observations that comprise each RAP. These will be verified and will form the key aspects of the simulation system.

The primary motivation of this chapter is to document the development of the simulation approach for travel demand forecasting. It first focuses on design issues related to the development of the modeling system and then considers the details of particular sub-models. The classification provides a means of identifying the choice probability distributions associated with each RAP and its underlying activity type. location. and duration dimensions. 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.

Figure 5.1 provides an overview of the model as outlined here. 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. **Figure 5.2** provides a flowchart of the *first stage* of the MCS, which assigns a RAP to the individual based on the identified RAP likelihoods using a RAP Assignment Model (RAM). **Figure 5.3** outlines the *second stage*, simulating a 24-hour activity-travel pattern: minimally, a sequence of activities, each with a type, start time, duration, and location. It 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 the beginning time step, 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

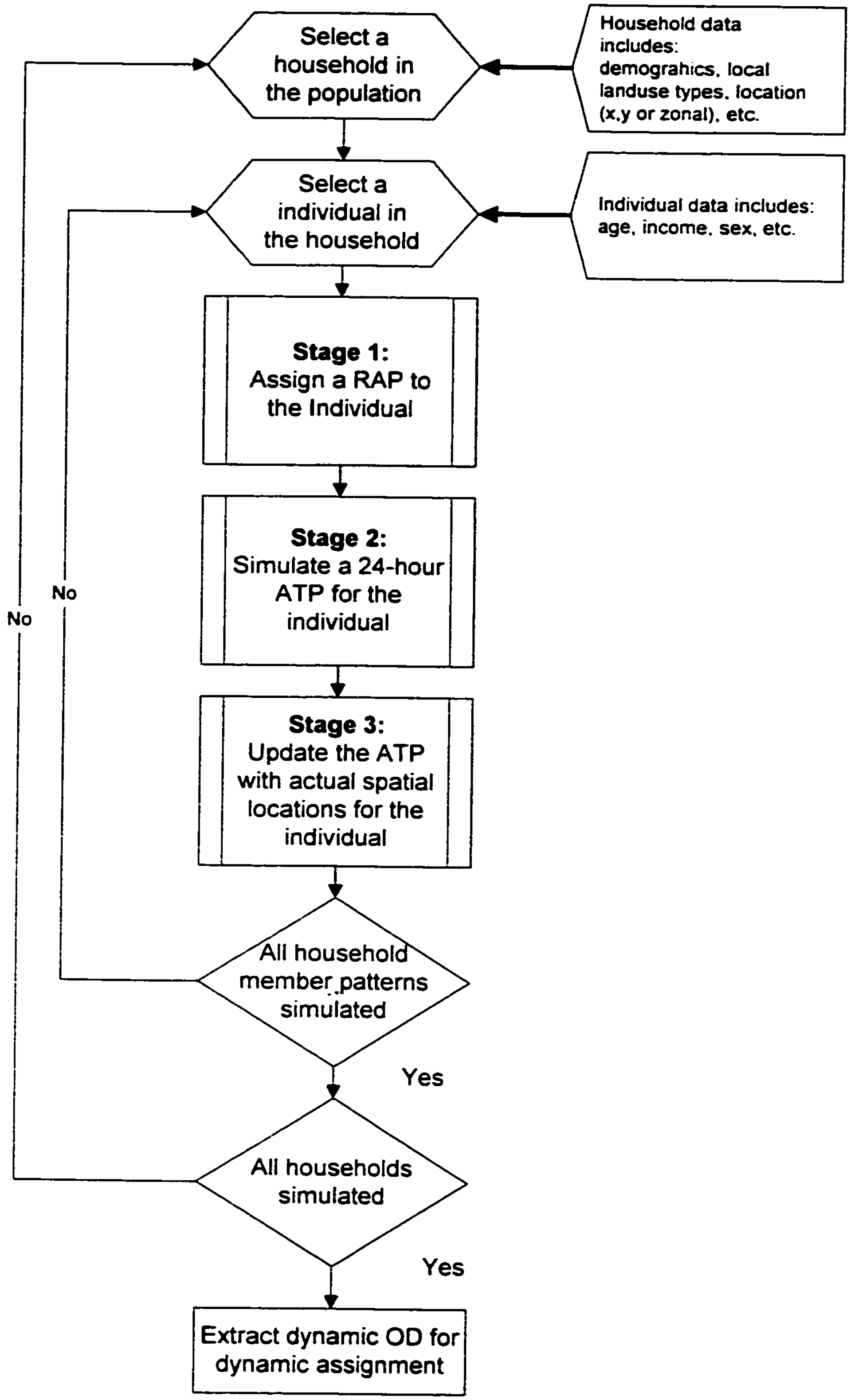

Figure 5.1. Model Overview

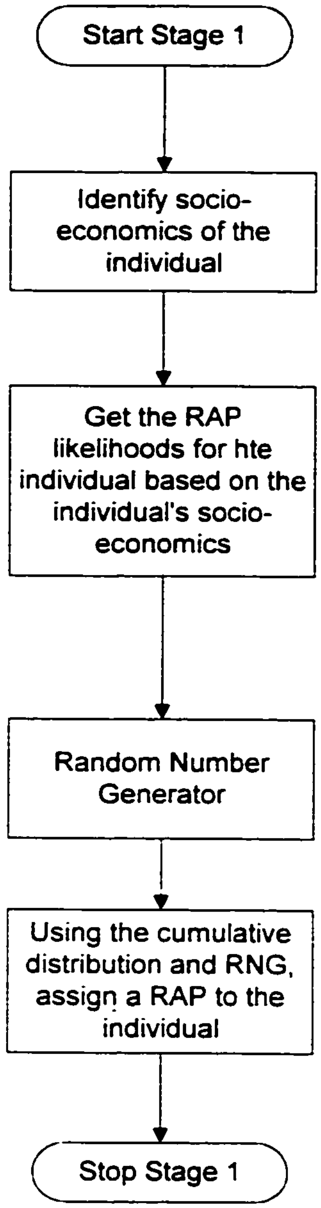

Figure 5.2. Stage 1

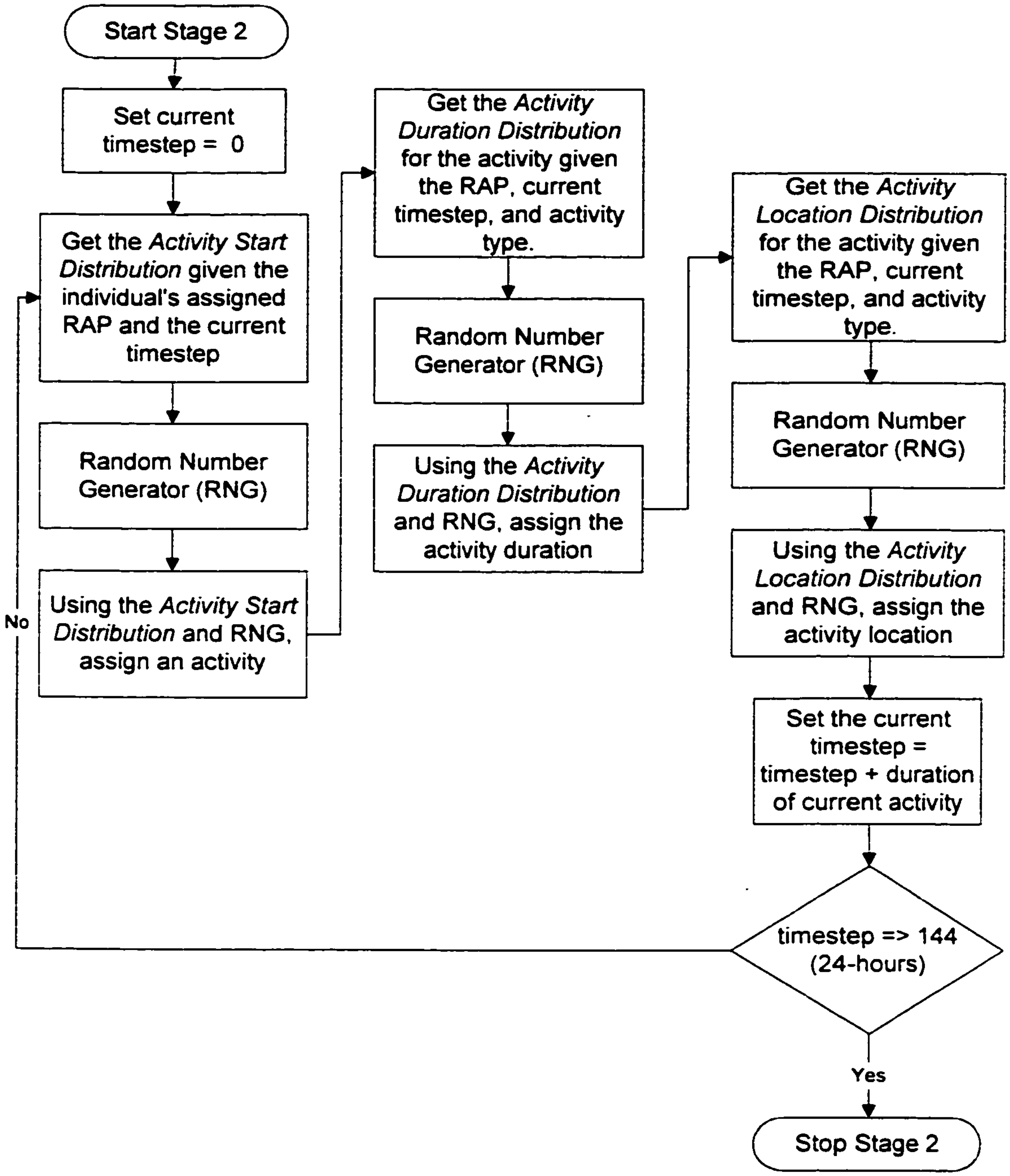

Figure 5.3. Stage 2

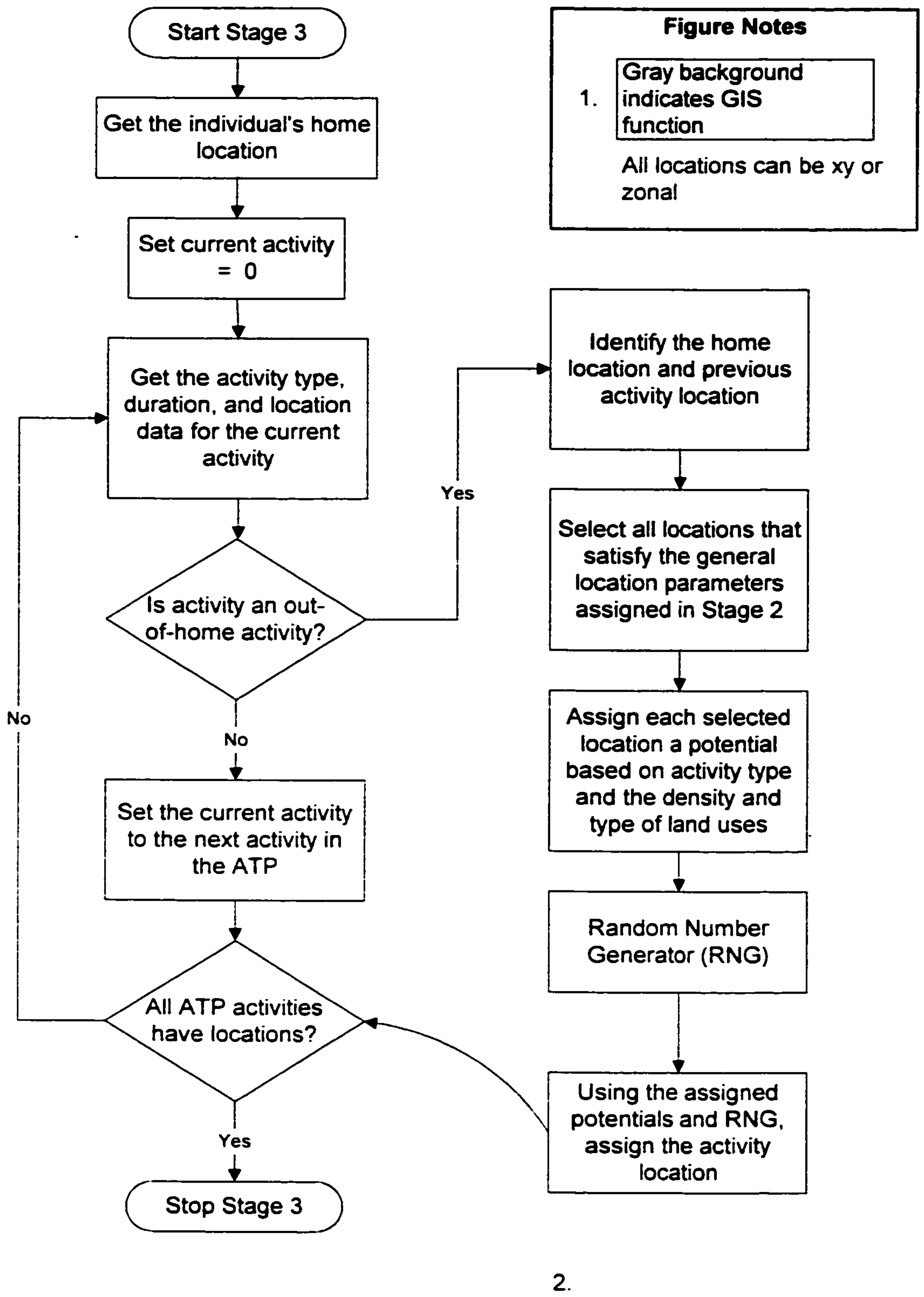

Figure 5.4. Stage 3

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 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 is solved in the implementation of the microsimulation. 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, it 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 *third stage* of the MCS updates the general location parameters with specific activity locations using a GIS updating procedure (see **Figure 5.4**). 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 each 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 (e.g., peak period) or time-based (e.g., 15 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.

5.3 DISTRIBUTION CONSTRUCTION

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 5.2**; here, the required distributions needed to simulate synthetic patterns and the details of their construction are documented.

5.3.1 Rap Assignment Model

The simulation approach requires that a target RAP first be specified for a selected individual; this is done through the Rap Assignment Model. This model must specify the probability that an individual with particular characteristics will engage in each identified RAP and is empirically estimated directly from the classification results. As a result, the structure of Rap Assignment Model is closely tied to the structure of the classification. In this case, the Rap Assignment Model categorizes individuals by employment status and age as shown in **Table 5.1**. As an example, 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; the target RAP can be randomly assigned. Alternately, extending the **Table 5.1** 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 5.1 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%

The remainder of this section will document the process of developing the requisite distributions for the Standard Work RAP of Adults Employed Full-time, herein referred to as Standard Work RAP. **Figure 5.5** shows the activity profile for the Standard Work

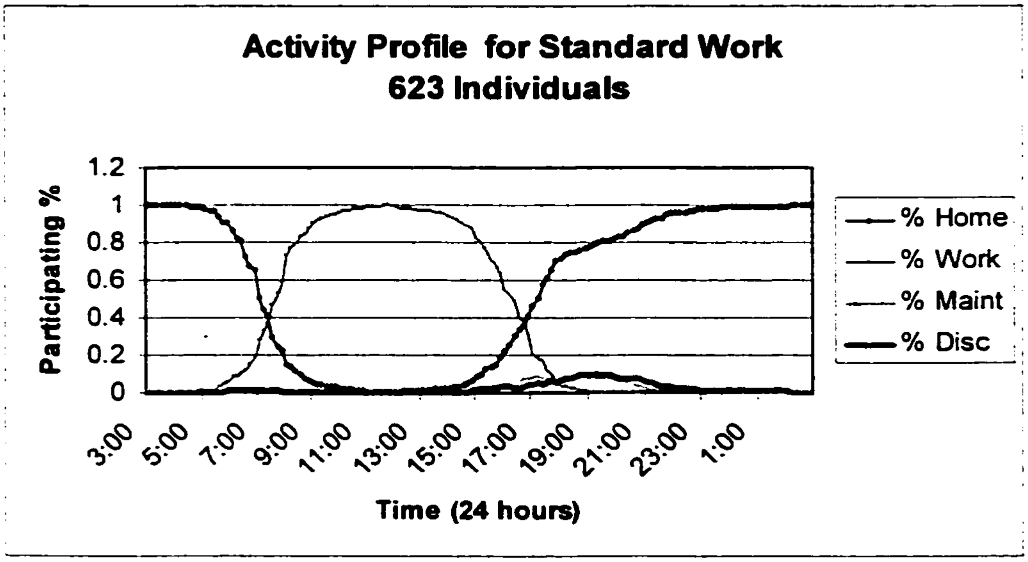

Figure 5.5 Activity Profile for Standard Work

RAP. The processes used to obtain the distributions for the Standard Work RAP are the same for the remaining RAPs and therefore are only described once. However, the distributions are in figures included in **Appendix A** for Adults Employed Full-time and in **Appendix B** for Adults Not Employed Full-time .

5.3.2 Activity Assignment Model

The activity assignment model is empirically constructed from the proportion of the RAP members that start each specified activity type (home, work, maintenance, and discretionary) at each time step. Because of the limited number of individual activity patterns from which the RAPs were estimated, the model was defined with a time window set at one-half hour. Thus, the model is constructed for each time step from the proportion of RAP members that start each specified activity within one-half hour of either side of the timestep in question. The probability that an individual engages in a

Home, Work, Maintenance, or Discretionary activity at a particular time step is derived empirically by the percentage of the specific activity starts *within one-half hour of the time step in question* for all the individuals that define the RAP. **Figure 5.6**

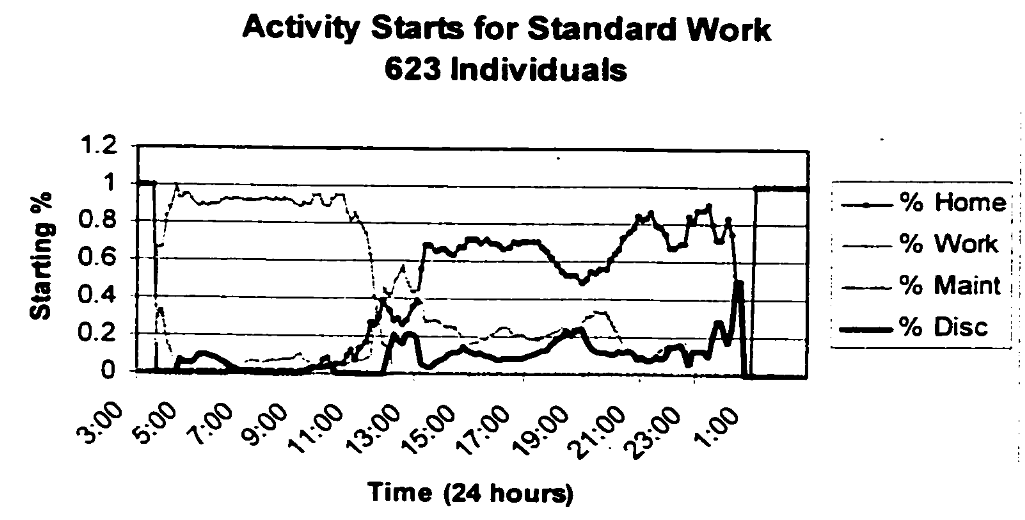

Figure 5.6 Activity Starts for Standard Work

provides a detailed profile of the mean proportion of activity starts by time step developed for the Standard Work RAP developed last chapter for 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 Work, Maintenance, Discretionary or Return Home activity. This results in an activity assignment model that can assign the likelihood that an individual participates in all possible activities by time step and randomly selects the specific activity from those likelihoods.

5.3.3 Activity Duration Model

Once the activity has been assigned, associated durations have to be sampled from the distributions associated with the target RAP. These distributions are derived in a similar fashion as the Activity Assignment Model. The average and standard deviation duration (minutes) and distance from home (miles) for each Home, Work, Maintenance, and Discretionary activity is specified at every time step for each RAP. These measures are empirically derived for the specific time step by averaging the duration and distance for each Home, Work, Maintenance, or Discretionary activity that starts *within one-half hour of the time step in question* for all the individuals that define the RAP. **Figure 5.7** provides a detailed profile of these derived mean activity durations by starting time step and activity type developed from the Standard Work RAP for 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 5.7** applied to a normal distribution. Statistical tests were conducted on the data that showed durations were distributed normally. The procedure used to simulate a duration simply inputs the mean and standard deviation into the random number generator. The output is a random number that conforms to the mean and standard deviation supplied. Thus, the method used to obtain a duration is easy to implement. It is also ingenious in its data requirements: the mean and standard deviation for the four activity durations that start "near" each time step.

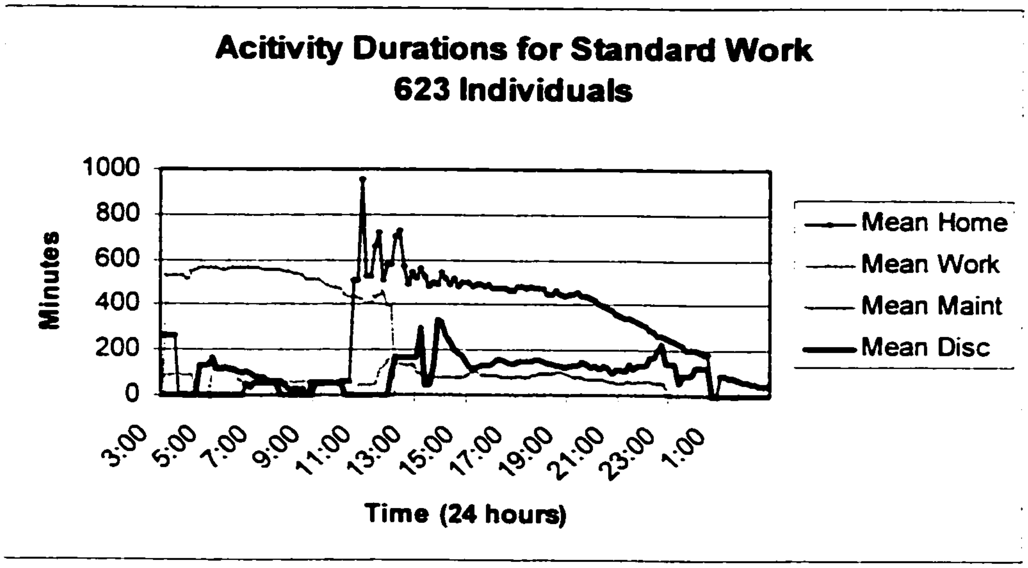

Figure 5.7 Activity Durations for Standard Work

5.3.4 Activity Location Model

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) through an Activity Location Model in a similar fashion as the Duration Model. The average (and standard deviation) distance from home for each Work, Maintenance, and Discretionary activity that starts *within one-half hour of the time step in question* is estimated for each RAP. **Figure 5.8** provides a detailed profile of the mean activity distances by starting time step and activity type developed for the Standard Work RAP. 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 5.8** using a normal distribution. Once an activity type, duration, and location are ascribed using the constructed models, a new activity type, duration, and location are randomly

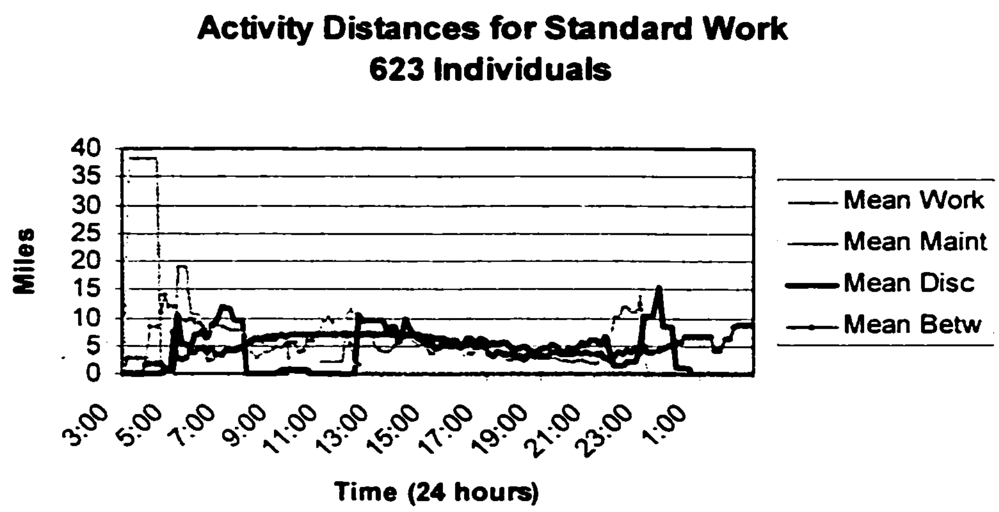

Figure 5.8 Activity Distances for Standard Work

selected at the time step when the previous activity is completed. This continues until the entire 24-hour activity-travel pattern is completed. The implementation and data requirements are the same as for the Activity Duration Model described earlier.

5.4 PROGRAMATIC SETUP

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 in order to execute the developed models. 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

These tables are used in the simulation of the first two stages of the microsimulation to assign a RAP to the individual and synthesize a provisional RAP.

For the third stage, 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 MapObjects (ESRI, 1999)components, providing a flexible approach for displaying, modifying, and manipulating network and land use coverages. Currently, distance is used as the measure rather than time primarily to facilitate the rapid development of the modeling system. Ideally, travel time could be substituted in future versions of the model, though it would require more detailed network impedance information by time of day in order to be implemented.
To illustrate the prototype microsimulation application developed, this section steps through a sample of the microsimulation approach outlined earlier in this chapter. The

distributions are developed from the Portland Metro's activity survey, network, and land use databases. As many screenshots as possible are provided to give a look and feel to the microsimulation application, primarily in the third stage of the microsimulation. When screenshots are not possible, particularly in the first and second stages that involve database queries and data crunching, a sample that demonstrates the internal logic of the application is provided to best understand the process. Only one individual from the household is specifically included because the process for simulation individual Activity Patterns is identical, with the only difference being the specific distributions used.

Before the simulation of the RAP can begin, the microsimulation must first select the household whose activity patterns are to be simulated. **Figure 5.9** shows a screenshot of the selected household, marked by the large, white "H". One should notice that a number of "layers" or ESRI shapefiles are included in the viewed application. These include the local employment, transportation, and demographic (by TAZ) data. Once the household is selected, the database is queried regarding the socio-economic statistics of the household including the number of individuals residing, the sex and ages of these individuals, the household income, and number of vehicles. This data can be obtained either from detailed census-type surveys or synthetic data statistically derived from coarser census data. Next, for each individual in that selected household, a RAP is assigned. **Table 5.2** illustrates the assignment of the RAP for the Male Adult using the Adult RAP assignment model developed earlier in **Table 5.1** and obtained from a database query. In this instance, the Male Adult from the household is assigned to the Standard Work RAP.

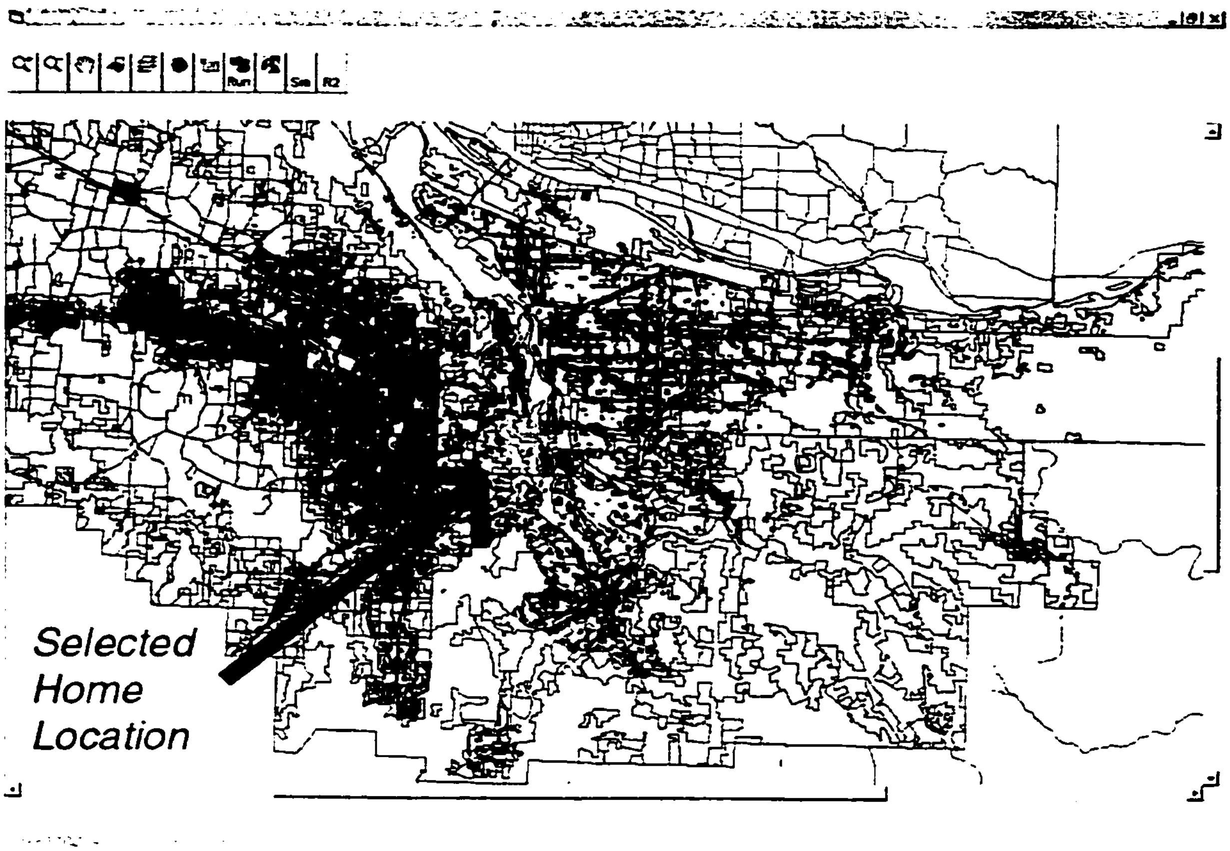

Figure 5.9 Screenshot of the Simulation with the Selected Household

Steps	Execution
A. From the Selected Household, Obtain its Socio-economic Characteristics	Middle Income (45K – 55K) Male Adult (29, Employed Full-time) Female Adult (27, Not Employed) Female Child (2, Does not Attend School)
B. Select An Individual Select an Individual from the household.	In this example, start with the Male Adult.
C. Assign RAP Probabilities The individual is stratified into Full-time Worker Category with the following RAP participation likelihoods:	Standard Work – 33% Power Work – 8% Multiple Work –40% Late Work –4% Various Short Activities –15%
D. Randomly Assign RAP from RAP Probabilities RAP (SW, PW, MW, LW, & VSA 33, 41, 81, 85, & 100)	Uniform Random Number (Σ = 33, 41, 81, 85, & 100) = 15 Assigned RAP for Male Adult (29) = STANDARD WORK
E. Repeat steps A-D for all household members.	

Table 5.2 Simulate a 24-hour Pattern RAP for All Adult Employed Full Time Assigned to the Standard Work RAP

Next, **Table 5.3** illustrates the simulation of the 24-hour Activity Pattern from the Standard Work RAP distributions for the Male Adult. The simulation starts at 3 AM of the day in consideration and ends the next day at 3 AM: the individual starts at home; leaves for work at 7 AM; leaves work at 4:40 PM; and finally stays at home for the rest of the simulation period. This is the expected result as the Standard Work RAP is largely a straightforward Home-Work-Home pattern and the likelihood is that most individuals assigned to this RAP would participate in that activity pattern.

Figure 5.10 shows a screenshot of the simulation identifying all the potential spatial locations for the work activity the Adult Male leaves home for at 7:00 AM. Distance rather than travel time is used in the current application so the potential locations are identified by selecting all TAZ's that are 9 miles from the home location. Once selected, the retail and total employment figures of each zone are used as the potentials for selecting that zone depending on the type of activity. If the activity is a work activity, then total employment is used; if the activity is maintenance activity, then retail employment is used; and if the activity is a discretionary activity, a combination of retail and other employment is used. Once the potentials for each zone is set and total potentials for all zones calculated, they are converted to probabilities (zone "x" potential / total potentials) and a zone is randomly selected in a Monte Carlo fashion. **Figure 5.11** shows a screenshot of the selected zone. Once the entire activity pattern of the individual is simulated, the same process is repeated for all members of the household and further all households for the region under consideration. At this point in the simulation, there is enough information to construct a dynamic Origin-Destination trip table for input into a dynamic traffic assignment model. Once all the patterns are input into a dynamic traffic assignment model. the actual travel times can be calculated for each pattern (**Figure 5.12**).

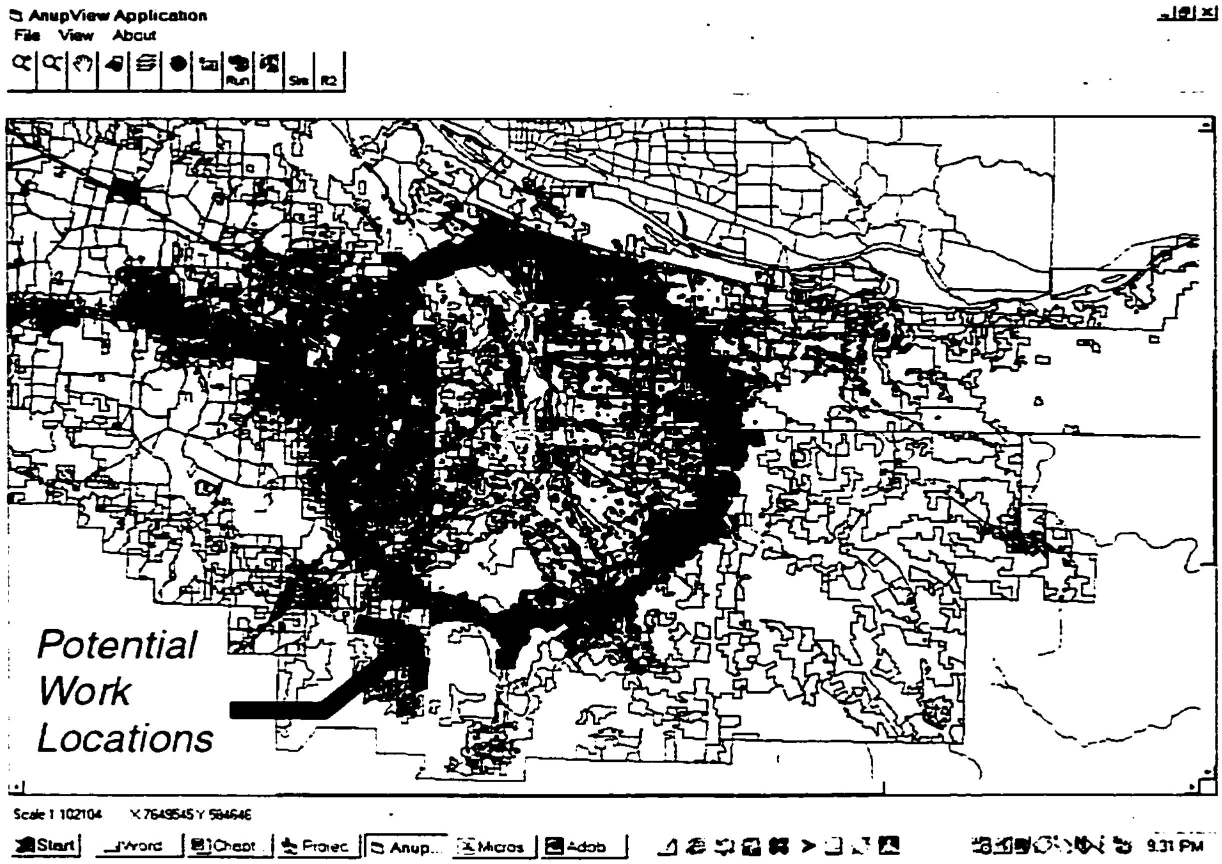

Figure 5.10 Screenshot of the Simulation Identifying all Potential Spatial Locations for the Work Activity

CALCULATIONS	DECISION
RAP: Standard Work	ASSIGNED IN PREVIOUS STAGE
Time = 3 AM (Timestep 1) 1. ACT W, M, D, & H 0, 0, 0, & 100 2. DURATION (min.) μ= 261, σ= 66 3. MILES FROM HOME	 Uniform Random Number (Σ = 0, 0, 0, & 100) = 45 ACTIVITY = HOME Random Number (μ= 261, σ= 66) = 240 DURATION = 240 minutes MILES FROM HOME = 0 miles (HOME)
Time = 7AM (Timestep 24) 1. ACT W, M, D, & H 92, 98, 98, & 100 2. DURATION (min.) μ= 557, σ= 60 3. MILES FROM HOME μ= 8, σ= 7	 Uniform Random Number (Σ = 92, 98, 98, & 100) = 54 ACTIVITY = WORK Random Number (μ= 557, σ= 60) = 580 DURATION = 580 minutes Random Number (μ= 8, σ= 7) = 9 MILES FROM HOME = 9 miles
Time = 4:40 PM (Timestep 82) 1. ACT W, M, D, & H 0, 21, 30, & 100 2. DURATION (min.) μ= 469, σ= 228 3. MILES FROM HOME	 Uniform Random Number (Σ = 0, 21, 30, & 100) = 45 ACTIVITY = HOME Random Number (μ= 469, σ= 228) = 620 DURATION = 620 minutes MILES FROM HOME = 0 miles (HOME)
Time = 3 AM (Timetep 144): STOP	

Table 5.3 Simulate a 24-hour Pattern RAP for AN Adult Employed Full Time Assigned to the Standard Work RAP

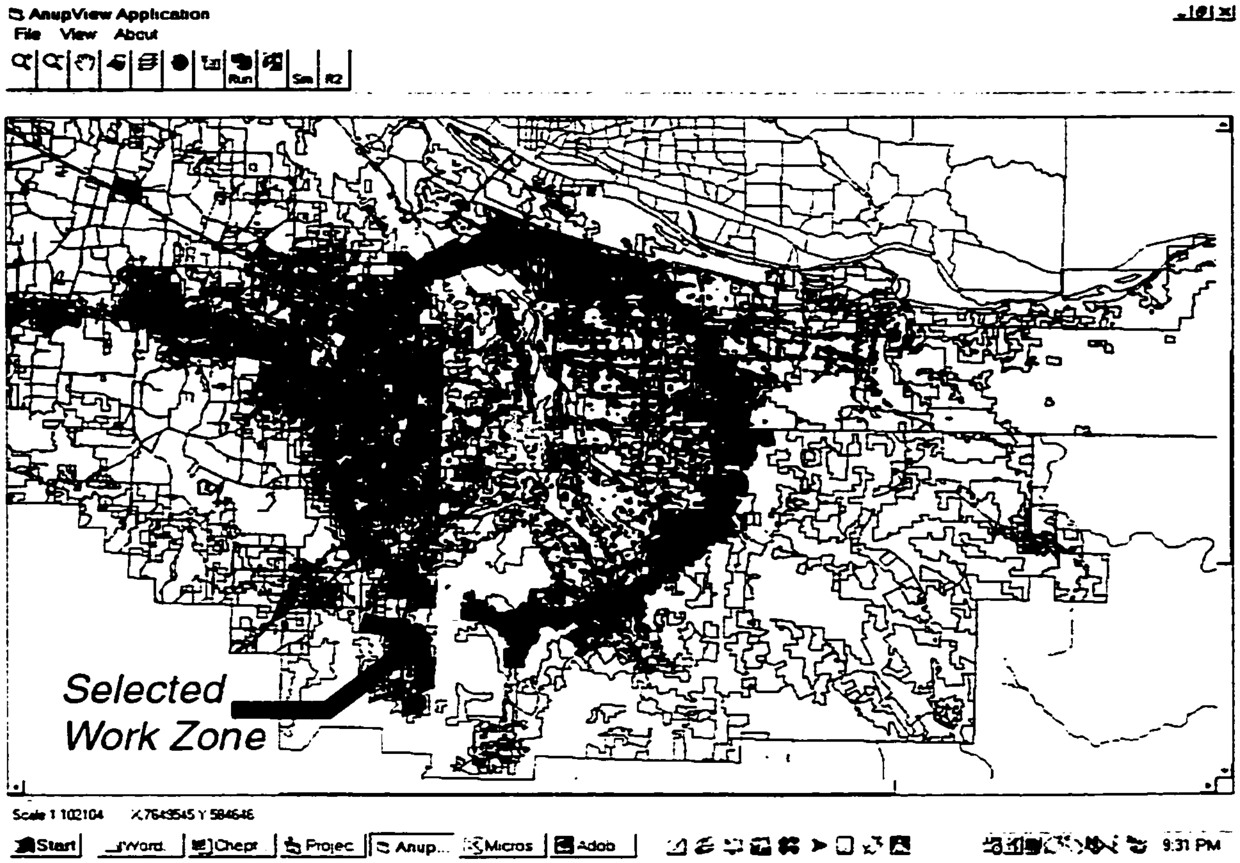

Figure 5.11 Screenshot of the Simulation After Selecting the Work Zone

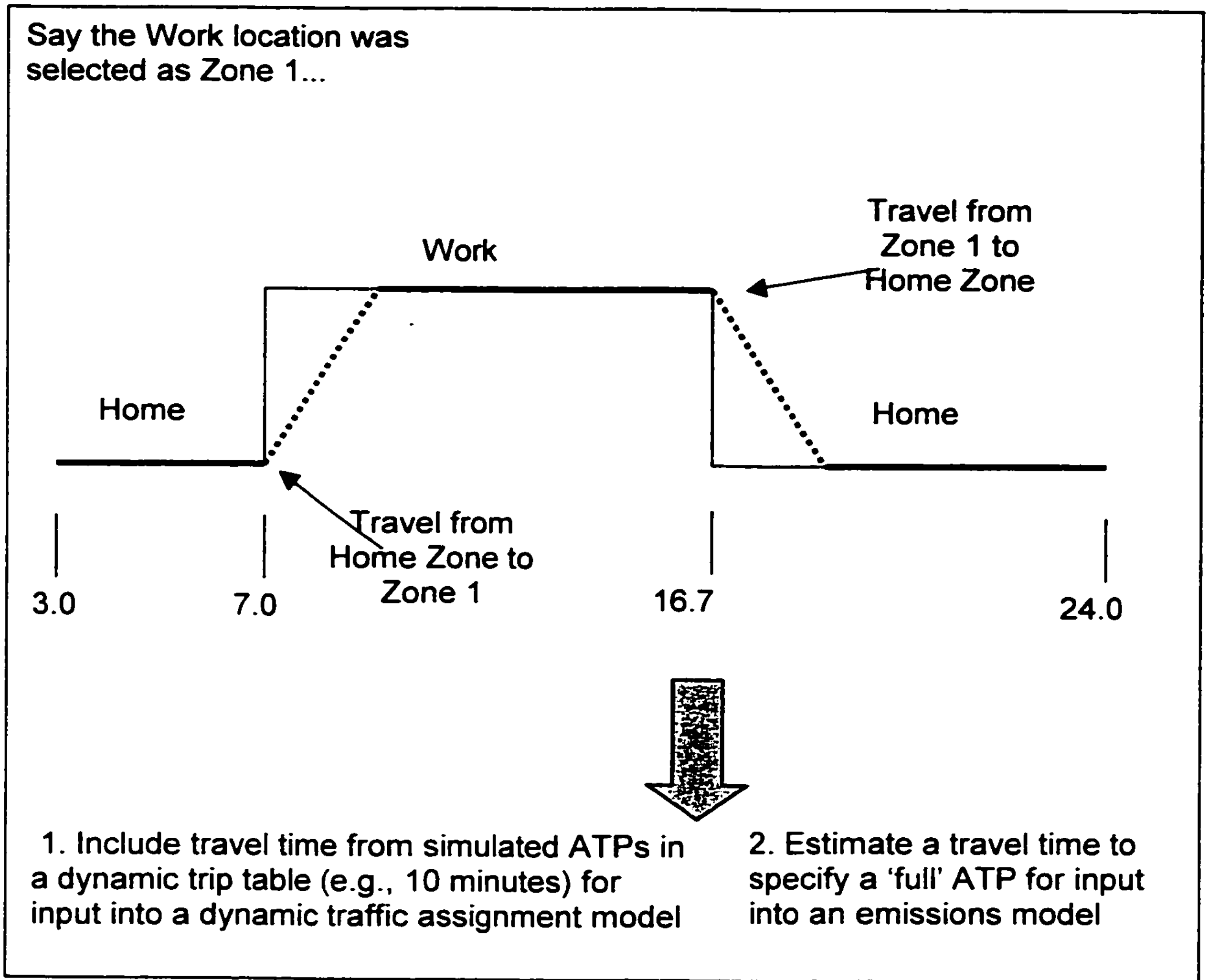

Figure 5.12 Adding Travel To The Synthesized ATP

5.5 SIMULATION RESULTS

An application of the simulation approach was conducted to test its overall performance in synthesizing activity-travel patterns. The simulation approach was applied to synthesize one-hundred 24-hour individual activity-travel patterns that consisted of activity type, start time, duration, and distance from home for each identified Adult RAP. As an example, **Figure 5.13** provides the aggregate activity profile of the 100 synthetic patterns simulated from the Standard Work RAP. **Figure 5.14** shows the activity distances of the synthetic patterns, while **Figure 5.15** shows the locations of the activities. When compared to the original pattern data from the last chapter, one can see the synthetic pattern statistics compared well, within the actual profile and distances. The same is true for the other RAPs, thought the individual figures are not shown here due to space constraints.

Several sets of statistics were calculated with the intention of analyzing the accuracy of the results. First, the activity profile (activity participation by time step) of the original RAP activity profile (**Figure 5.5**) is compared to aggregated activity profile of the 100 synthesized patterns (**Figure 5.14**). 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 RAP patterns (**Table 5.9**).

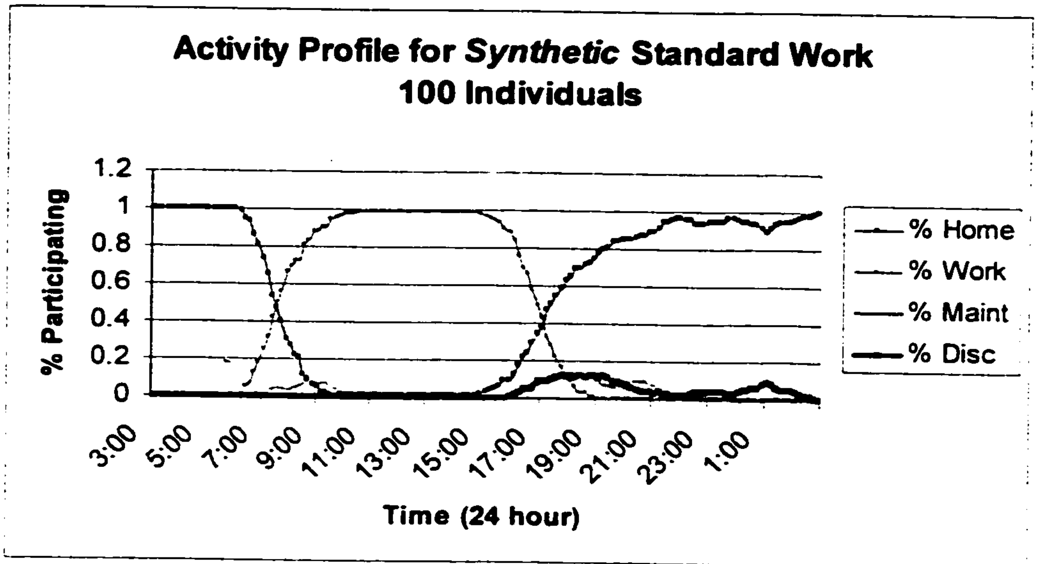

Figure 5.13 Activity Profile for Synthetic Standard Work

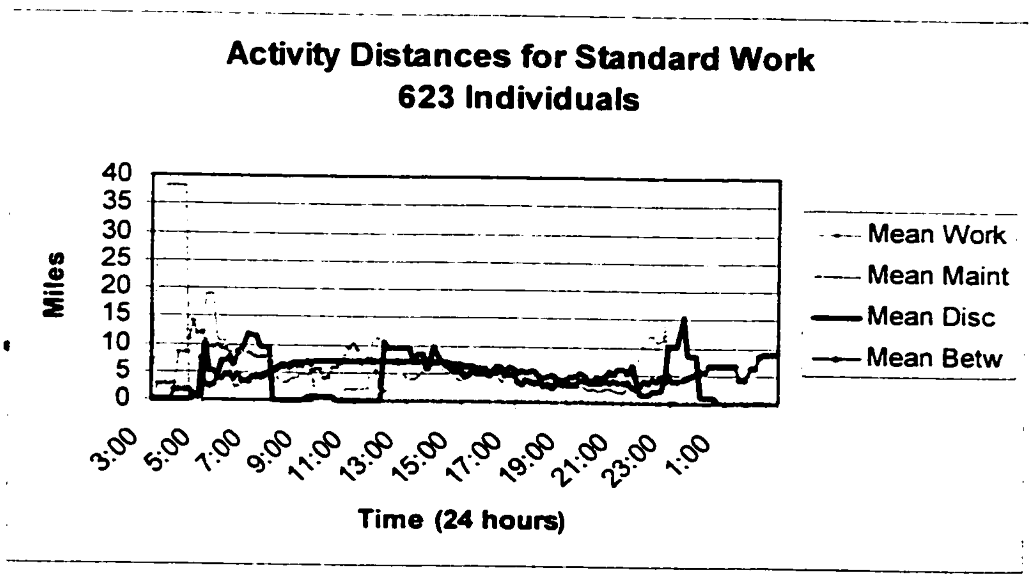

Figure 5.14 Activity Distances for Synthetic Standard Work

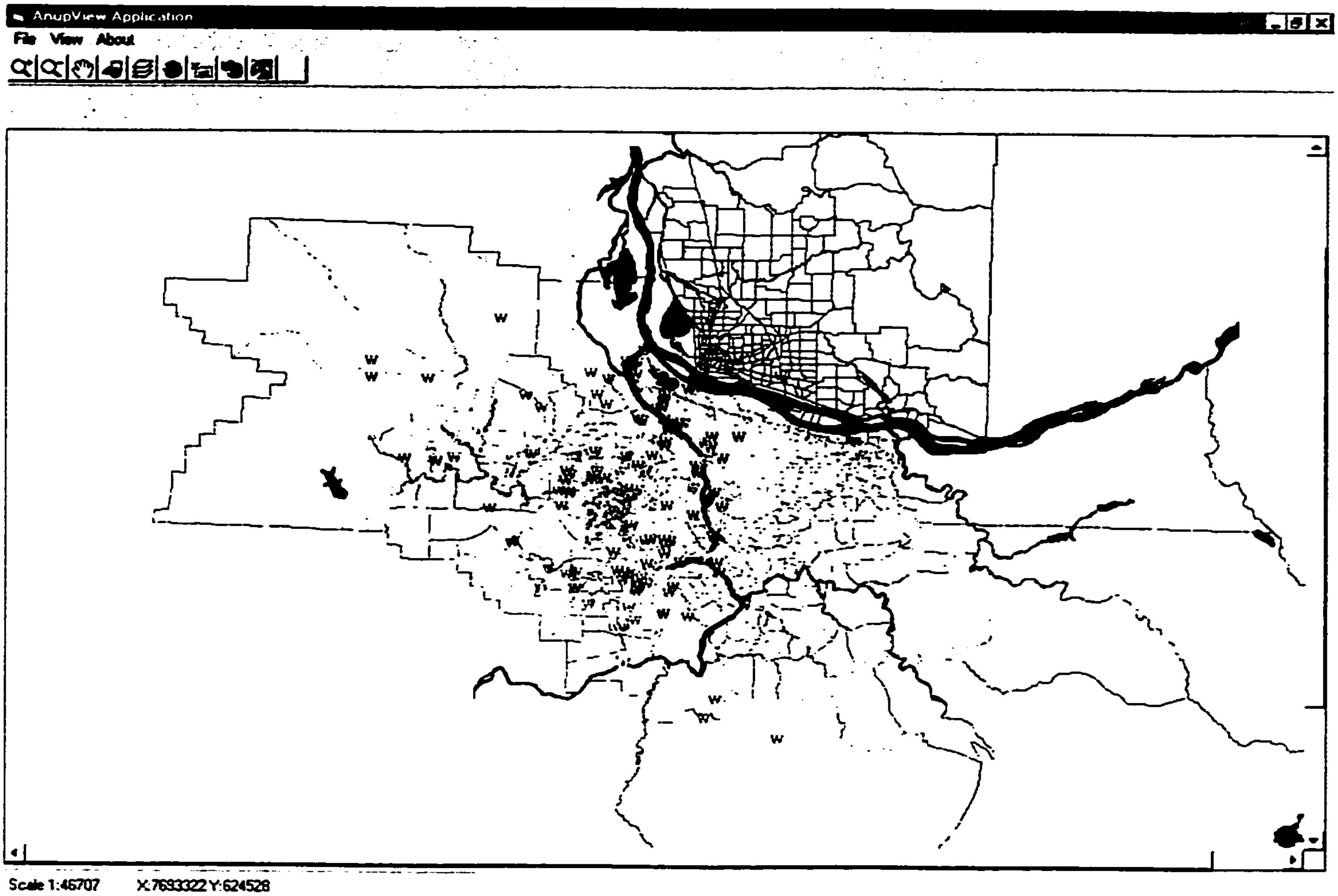

Figure 5.15 Screen Shot of the Simulation Approach

The error formulas are specified below:

Mean Error (ME) : $\Sigma_{I=1,N} (A_i - S_i) / N$

Absolute Error (MAE): $\Sigma_{I=1,N} |A_i - S_i| / N$

Root Mean Square Error (RMSR): $\Sigma_{I=1,N} (A_i - S_i)^2 / N$

where N equals the Number of Time Steps

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.

5.5.1. Adults Employed Full-Time

The ME, MAE, and RMSE measures for the Adults Employed Full-time (**Table 5.4**) indicate that the activity profiles of the forecasted patterns are, in aggregate, a good representation of the activity profiles of the actual patterns. In general, the synthetic patterns are similar to the actual RAPs from which they were produced. One aberration to this is that the Standard Work RAP errors are noticeably higher than for the other RAPs. Specifically, the ME shows that there is a slight bias toward out-of-home Work, Maintenance, and Discretionary activities over Home activities. But overall, the errors are quite low on average.

Table 5.5 shows the percentage of time steps that the synthetic patterns are different from the originating RAP. By and large, a great majority of the activities forecasted for each time step are within 5% of the observed activity profiles for each RAP, with a majority often in the <1% range. By RAP, the Standard Work RAP performed the worst with a large portion of time steps with errors greater than 5%. It seems that the Home and Work activities are interchanged at a number of time steps indicating a systematic error in the activity start distribution (either a too early start or a too late start). The Power Work, Late Work, and Various Short Activities RAPs show a much better result, particularly with respect to the accuracy of the simulated work activity being within "less than 1%" of the specified activity participation range close to 100% of the time. Clearly, a number of the RAPs have a noticeable percentage of time steps with an error "greater than 5%", but overall, the results show that the simulation produces individual patterns that are aggregately "close" to the original RAP.

Table 5.6 shows how the synthesized activity chains compare to the observed activity chains for each RAP. This statistic gives an idea of how the simulation fares at a disaggregate, tour-based level. Note that in **Table 5.6**, the "X" represents any maintenance or discretionary activity and that sequentially repeating activities are indicated with the activity type followed by a "*". For instance, the "H*W*H*" indicates that an individual engaged in one or more Home activities, followed by one or more

Work activities, followed by one or more Home activities. Seven tour types are compared, including four explicitly specified single work tours and three general tour categories for any non-specific tour (zero, one, and two-plus). The results show that on a disaggregate level, the simulation approach is able to produce a number of distinct tour types.

Table 5.4 Calculated Error Measures for Synthesized RAPs for Adults Employed Full Time

	Standard Work			Power Work			Multiple Work			Late Work			Various Short Acts		
	ME	*MAE*	*RMSE*	*ME*	*MAE*	*RMSE*	*ME*	*MAE*	*RMSE*	*ME*	*MAE*	RMSE	*ME*	*MAE*	*RMSE*
Activity															
Home	-1.52	3.69	5.95	0.01	0.04	0.06	0.00	0.03	0.04	0.03	0.04	0.06	-0.06	0.08	0.10
Work	0.98	3.15	4.99	-0.01	0.01	0.01	-0.02	0.03	0.06	-0.03	0.03	0.05	-0.03	0.03	0.05
Maintenance	0.46	1.39	2.11	0.00	0.01	0.02	0.01	0.02	0.04	0.00	0.01	0.02	-0.04	0.04	0.05
Discretionary	0.08	1.09	1.70	-0.01	0.04	0.05	0.00	0.01	0.01	0.00	0.01	0.02	0.13	0.13	0.17

Table 5.5 Percentage of Time Steps Where the Synthetic RAP Activity Participation is Within the Specified Range of the Observed RAP for All Identified Adults Employed Full Time RAPs

	Standard Work				Power Work				Multiple Work				Late Work				Various Short Acts			
	Hom.	Work	Main.	Disc.	Hom.	Work	Main.	Disc.	Hom.	Work	Main.	Disc.	Hom.	Work	Main.	Disc.	Hom.	Work	Main.	Disc.
< 1%	44	44	55	71	67	100	78	62	35	45	50	58	68	100	78	63	68	101	78	63
1% - 2%	16	19	16	13	6	0	6	6	26	14	23	27	6	0	6	6	6	0	6	6
2% - 3%	7	3	15	8	3	0	3	4	13	13	5	11	3	0	3	4	3	0	3	4
3% - 4%	4	4	4	2	1	0	5	6	9	3	7	4	1	0	5	6	1	0	5	6
4% - 5%	1	4	3	2	2	0	1	8	6	4	4	0	2	0	1	8	2	0	1	8
> 5%	29	24	7	4	20	0	8	14	13	22	11	0	19	0	7	13	20	0	8	14

Table 5.6 Synthetic Vs. Observed Activity Chains for Adults Employed Full Time

	Standard Work		Power Work		Multiple Work		Late Work		Various Short Activities	
	Estimated	*Observed*	*Estimated*	*Observed*	*Estimated*	*Observed*	*Estimated*	*Observed*	*Estimated*	*Observed*
Chain Type										
H*W*H*	50%	50%	76%	73%	24%	7%	54%	36%	18%	5%
H*X*W*H*	25%	3%	21%	1%	11%	1%	10%	3%	15%	1%
H*W*X*H*	7%	14%	2%	13%	2%	1%	15%	8%	1%	4%
H*W*X*W*H*	0%	0%	0%	0%	27%	37%	2%	13%	0%	1%
Other: 1 Sojourn	5%	6%	0%	2%	20%	18%	1%	0%	25%	0%
Other: 2+ Sojourns	13%	27%	1%	11%	1%	36%	7%	25%	16%	48%

Unfortunately, while it can produce a range of different tours, the results also indicate that more accuracy is needed in the simulation to correct for bias against multiple tours. It seems that more elementary activity chains are synthesized with greater accuracy than more complex, multi-tour patterns. This is particularly apt with respect to the patterns estimated from the complicated Work-Maintenance and Various Short Activities RAPs contrasted with the simpler patterns estimated from the Standard Work, Late Work, and Power Work RAPs. In the best case scenario, the Standard Work RAP, there is an under prediction of multiple tours by a factor of two (13% predicted versus 26% observed). In the worst case scenario, the Work-Maintenance RAP, the under prediction is by a factor of 36 (1% predicted versus 36% observed).

5.5.2. ADULTS NOT EMPLOYED FULL-TIME

The ME, MAE, and RMSE measures for the Adults Not Employed Full-time (**Table 5.7**) indicate that the activity profiles of the forecasted patterns are again, in aggregate, a fairly good representation of the activity profiles of the actual patterns. The errors are very small on a percentage basis, on the order of less than one percent. Both this and the previous results for the ME, MAE, and RMSE show that the simulation framework is successful in producing patterns similar to the original RAPs.

Comparisons of the activity profile by time steps of the original RAP versus synthetic averages also gives support the contention that the simulation method does well in aggregate. For instance, a large number of "less than 1%" time steps exist that shows the percentage of time steps that the synthetic patterns are different from the observed for the ranges indicated in **Table 5.8**. A large majority of the activities forecasted for each time step are within 5% of the observed activity profiles for each RAP, with a majority often in the <1% range. By RAP, the Work/School RAP performed the worst with a large portion of errors greater than 5% for Home activities. However, for the other RAPs, the majority of the errors were "less than 1%" within the specified activity participation range closer to the 100% range most of the time.

Table 5.7 Calculated Error Measures of Synthesized Adults Not Employed Full Time RAPs Compared to the Observed Adults Not Employed Full Time RAPs

	Work/School			Maintenance			Discretionary			Various Short Acts		
	ME	*MAE*	*RMSE*	*ME*	*MAE*	*RMSE*	*ME*	*MAE*	*RMSE*	*ME*	*MAE*	*RMSE*
Activity												
Home	0.02	0.05	0.08	-0.02	0.03	0.04	0.00	0.05	0.00	-0.02	0.03	0.04
Work	-0.03	0.05	0.08	0.00	0.00	0.00	-0.02	0.07	0.15	0.00	0.00	0.00
Maintenance	0.01	0.02	0.02	0.01	0.02	0.03	0.01	0.04	0.09	0.01	0.02	0.03
Discretionary	0.00	0.01	0.02	0.00	0.01	0.01	0.01	0.02	0.02	0.00	0.01	0.01

Table 5.8 Percentage of Time Steps Where the Synthetic RAP's Activity Participation is Within Range of the Observed RAPs for Adults Not Employed Full Time

	Work/School				Maintenance				Discretionary				Various Short Acts			
	Home	Work	Maint	Home	Work	Maint	Disc.	Disc	Home	Work	Maint	Disc.	Home	Work	Maint	Disc.
< 1%	23	83	63	87	98	63	81	96	68	101	78	63	87	98	63	81
1% - 2%	16	3	15	5	2	9	8	5	6	0	6	6	5	2	9	8
2% - 3%	9	3	7	1	0	8	7	0	3	0	3	4	1	0	8	7
3% - 4%	7	2	8	1	0	6	4	0	1	0	5	6	1	0	6	4
4% - 5%	5	3	3	3	3	0	3	0	2	0	1	8	3	0	4	1
> 5%	40	6	5	3	15	0	3	0	20	0	8	14	3	0	11	0

Table 5.9 Synthetic Vs. Observed Activity Chains for Adults Not Employed Full Time

	Work/School		Maintenance		Discretionary		Various Short Acts	
	Estimated	*Observed*	*Estimated*	*Observed*	*Estimated*	*Observed*	*Estimated*	*Observed*
Chain Type								
0 Sojourns*	2	0	9	1	12	2	43	9
1 Sojourn	87	61	81	52	74	51	56	75
2+ Sojourns	11	38	10	47	14	47	1	16

*Note, 0 Sojourn tours exist because only those individuals who did not travel were thrown out. Those individuals who traveled, but did not participate in an outside activity as a result of the travel were still included in the sample (e.g., a drop-off or pick-up trip).

The results were also analyzed at the more disaggregate, tour-based level (**Table 5.9**) by comparing zero, single, and multiple tours. Again, the outcome points out the primary weakness of the simulation methodology as constructed: multiple tours are underestimated by the model. This is particularly important with respect to the patterns produced by the Maintenance and Various Short Activities RAPs. A secondary limitation of the model is that zero tours are overestimated. The results demonstrate that on a disaggregate level, the simulation needs further refinement to reflect these shortcomings.

5.6 CONCLUSION

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 hypotheses presented early in the chapter suggested that the RAP classification offered a means of associating choice probabilities to each defined RAP as well as activity type, location and duration dimensions for each RAP. Moreover, these distributions were suggested as a basis to simulate activity-travel patterns.

Taken as a whole, the results are encouraging as they show that the simulation model developed does produce patterns that, on average, satisfy the key hypotheses outlined in the beginning of the chapter. The model (1) replicates the overall distribution of the representative activity-travel patterns; (2) replicates the distributions of the characteristics within each of the representative activity-travel patterns; (3) adheres to the requisite spatial and temporal constraints; and (4) provides 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. The major shortcoming of the approach is that complex tours are not adequately modeled. While the results are far from ideal, they do represent an order of magnitude leap in the ability of travel demand models to reflect trip chains and multiple tours.

CHAPTER 6

EVALUATION AND SUMMARY

6.1 SUMMARY

The primary motivation for the research was to develop, construct, and test an activity-based simulation model to synthesize individual activity patterns in an accurate manner. Based on the results described in the previous chapters, the research was successful in achieving this goal. First, the simulation approach, at a high level, produces accurate activity-travel patterns. When the activity profile (activity engagement by time step) of the synthesized individual patterns is compared to the activity profile of the original RAP, they are extremely similar. At the same time, lower level comparisons of the activity chains between the synthesized and original patterns reveal a clear discrepancy that needs to be addressed. Specifically, simple, zero and single sojourn chains are overestimated and multiple sojourn activity chains underestimated. The primary factor for this deviance is that activities with short durations are difficult to synthesize. That is, the activity generation model, on which the simulation is based, is dominated by large duration activities. This results in the longer, dominate RAP activities (e.g., home and work) to be favored versus smaller, intermittent activities. Coupled with a lack of a high-level control on the construction of patterns, the simulation approach readily produces simple chains. That is, because the simulation is myopic and event-based, there is no controlling a fstructure that forces the pattern to be a specific chain type. A secondary factor that contributes to the bias towards simple chains is the limited number of data points from which to estimate activity starts. Because of the large number of time steps required to construct each RAP's activity start, duration, and distance distributions, a portion of the distribution may not have enough sample points given the limited number of patterns needed to construct the distributions. An effect of this is that a few travelers may have a disproportionate affect on the model, particularly for activities that start at odd times.

A secondary goal of the research was to make the simulation procedure comprehensive in order to include significant detail about the activity patterns, yet be straightforward for practitioners to understand, construct, and run. In the later respect, the model is quite extensive in the number of pattern elements that are explicitly modeled: activity type, duration, and location. Minimally, these three aspects need to be considered for that model to be successful. Moreover the model is flexible enough to be able to incorporate a number of socioeconomic, network, and land use variables that can be included easily into the simulation methodology, specifically be including them in the RAP assignment model. This allows the model to sensitive to a number of factors that are integral to transportation. For instance, the model system demonstrated in the previous chapters used employment status and age to relate to the RAPs and could be easily modified with other variables. On the former point, the RAP concept allows the model to be simple to understand and intuitively appealing. RAPs, in addition, have a number of benefits when used in transportation models: they have been shown to be temporally stable and can be identified using rule-based techniques that do not require calibration. By using a Monte Carlo Simulation technique is advantageous as it is not only extremely easy to apply, but the data (the underlying RAP distributions) required to run the models is also easy to construct.

6.2 EVALUATION OF THE RESULTS

Clearly, the model as constructed is not perfect. A number of shortcomings (both new and previously touched upon) were identified in the previous section and will be discussed in terms of identifying necessary improvements in the model. The most important problem to address is that the approach as implemented has no tour-based element to control for the structure and shape of the tour. Originally it was thought that the RAP structure was homogenous in relation to chaining behavior. Unfortunately, this is not the case, particularly for non work-based RAPs and the after-work activities for work-centered RAPs. As a result, chaining elements need to be included in the simulation. The question then turns to how to introduce chaining elements into the simulation. A number of paths exist within the framework of the approach described, constructed, and tested in the previous chapters to explicitly model chaining. The most likely, after the RAP type has been assigned to the individual, one of any number of "Chain Type" variables can also be simulated (chain construction: HWH; number of sojourns: etc.). Then the pattern can be simulated as outlined earlier with the caveat being that any pattern that does not conform to the assigned "Chain Type" variable would be disregarded and simulation restarted for that individual.

Another important limitation of the model is that intra-household constraints relating to the timing of activities, availability of household vehicles, joint activity participation, and others are also not fully considered in the model. 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. Finally, 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 as expressed in the previous chapter. GIS provides an important ability to do this in the model without too much alteration to the overall structure and code base of the model. The demonstration used Euclidean distance to assign locations. This can easily be updated within the GIS to include network distances modified to include time-of-day congestion information. Additionally, an iterative or dynamic framework equilibrating the activity locations with the actual travel times would need to be introduced in order for feedback to be modeled. This point is currently being investigated.

6.3 FUTURE RESEARCH

In addition to the immediate improvements outlined in the last section, there are a number of areas which need to be explored and extended concerning this dissertation research. More detailed model development and improvement is required before the simulation approach presented can replace current forecasting methodology. The primary focus of future research should be to improve the accuracy of the simulation approach's foundation by exploring a number of areas in the model framework.

First, the simulation approach needs to improve the Activity Assignment Model in order to better reflect actual trip chaining. A key change proposed for subsequent development includes introducing a "memory " component to predict the choice of activity by time of day. The method favored for further research and implementation would replace the current activity starts from the 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. So instead of simulating at a time step the likelihood that an individual engages in a home, work, maintenance, and discretionary activity, the model would simulate the likelihood that an individual engages in a home, work, maintenance, and discretionary activity given the previous activity that the individual was engaged.

Second, the simulation has to add the spatial dimension to the simulation, adding both home locations and actual activity locations. Figure 4.6 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 are clear in the figure, the general locations of maintenance (M) and discretionary (D) activities are coincident with the location of households (H).

Intra-household constraints relating to the timing of activities, availability of household vehicles, joint activity participation, and others need to be considered. Currently, activity-travel patterns initially are synthesized for each individual independent of other household members without 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.

Fourth, 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, several changes would need to be made. 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. Moreover, 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.

Finally, a great deal of work will be needed to apply the simulation approach to an actual planning region. 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.

Finally, a distributed computational framework offers great potential in extending this work. Through a distributed computational framework, the nature and logic of the simulation can be compartmentalized in such a fashion that certain tasks can be separated out. This would allow certain functions of the simulation such as the individual activity generation, location selection, and network traffic calculation to be assigned its own computational resources allowing a "cluster" of computers to deal with the entire simulation for a faster (possibly greater than real-time) result. Common techniques of clustering have become common in other agent-based simulations and could be incorporated into this simulation (including Beowolf clustering of inexpensive Linux machines).

6.4 CONCLUSION

This approach demonstrates that a distinct path towards developing an activity-based approach to modeling travel behavior. The approach builds upon previous research that identifies RAPs as patterns of activity and travel behavior that can be related to key transportation variables and have been shown to be temporally stable. The approach successfully applies a Monte Carlo simulation framework to the problem of synthesizing activity-travel patterns. The approach holds a number of distinct advantages over conventional trip generation models. First, because the conventional model produces trips as its standard output, a number of intermediate models and fixes are applied to address time-of-day and trip purpose. The process can be more accurate by introducing the full activity-travel patterns. The model is robust enough to address this by specifying complete activity-travel pattern as output. The patterns generated can be converted into a trip origin-destination table and be input directly into mode choice and route choice models. By introducing the proposed pattern generation model alongside conventional trip-based models, the acceptance and understanding of activity-based models will be hastened. The model constructed will also serve as the initial component of an ongoing effort at UC Irvine to produce an advanced activity-based microsimulation model aimed at replacing the entire conventional modeling process.

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APPENDIX A

POWER WORK, LATE WORK, WORK-MAINTENANCE AND VARIOUS SHORT ACTIVITIES DISTRIBUTIONS FOR ALL ADULTS WORKING FULL TIME

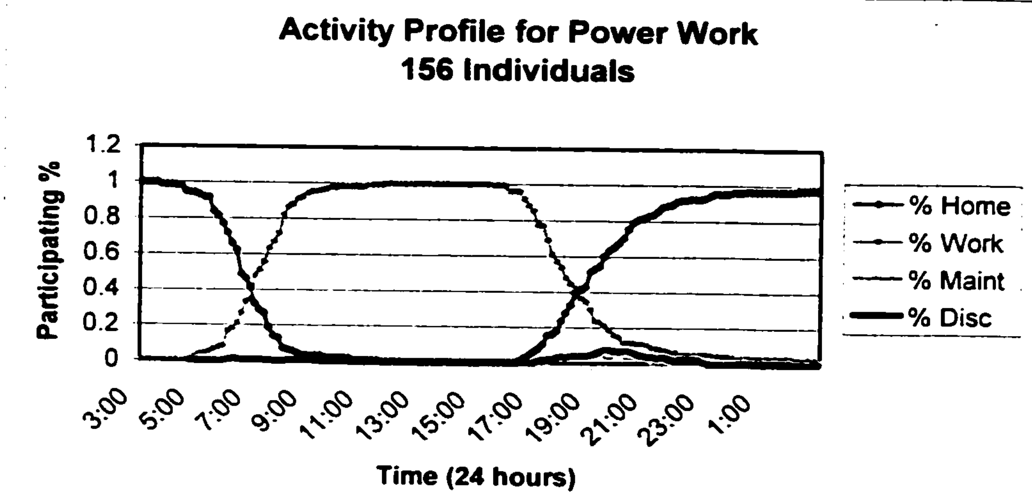

Figure A.1 Activity Profile for Power Work

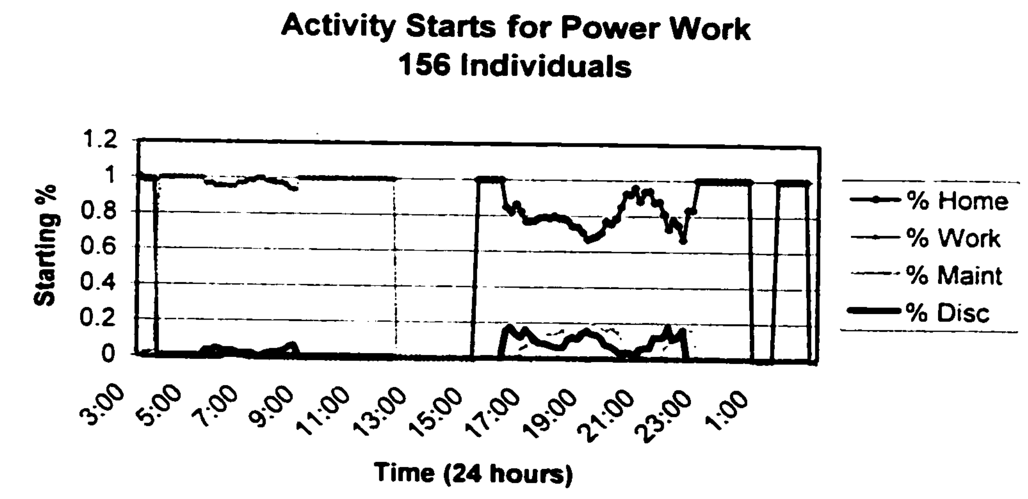

Figure A.2 Activity Starts for Power Work

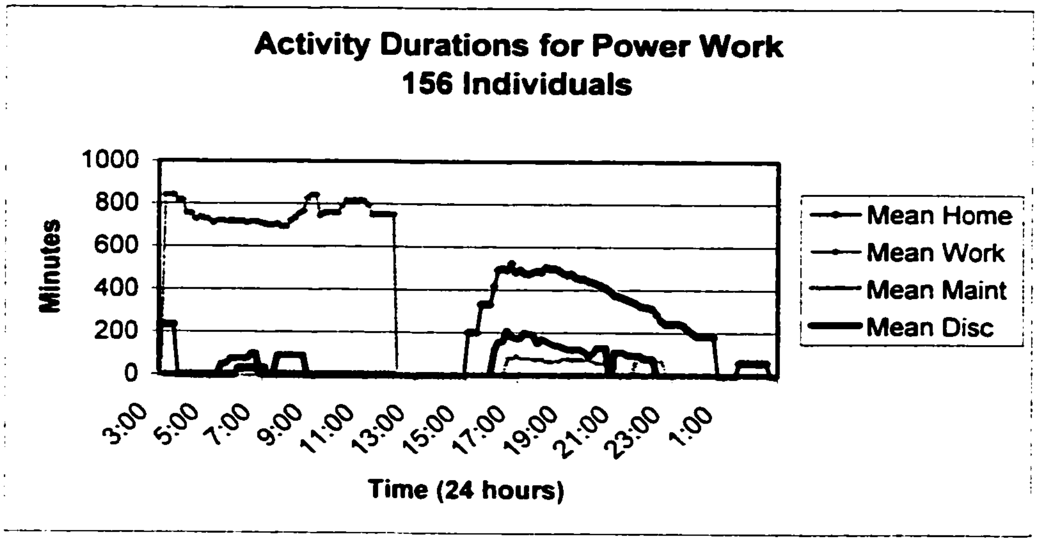

Figure A.3 Activity Durations for Power Work

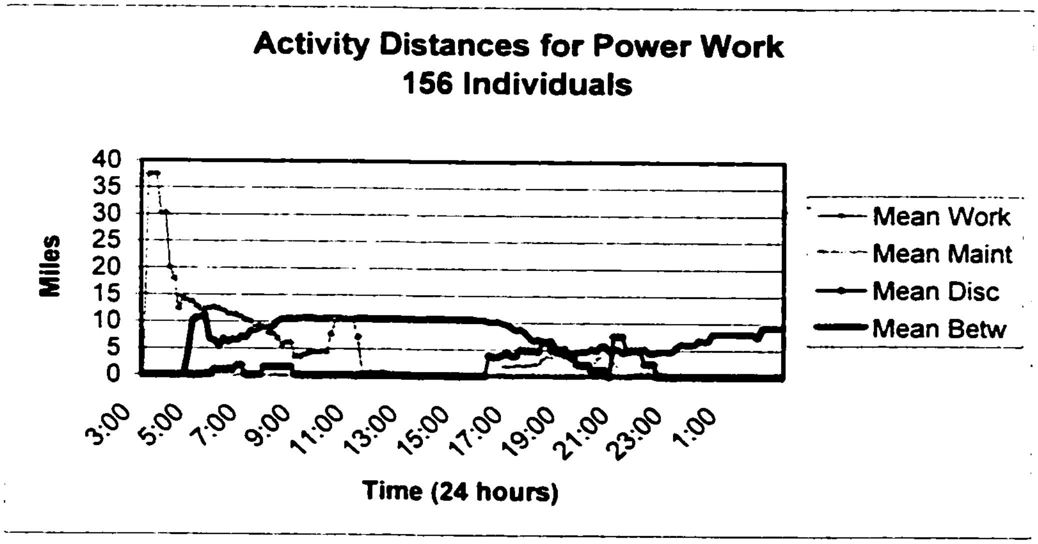

Figure A.4 Activity Distances for Power Work

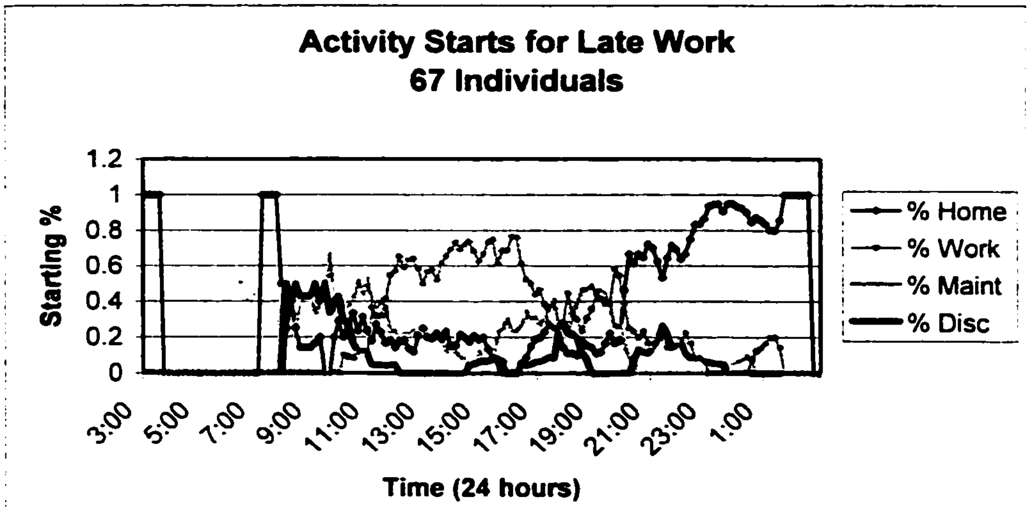

Figure A.5 Activity Starts for Late Work

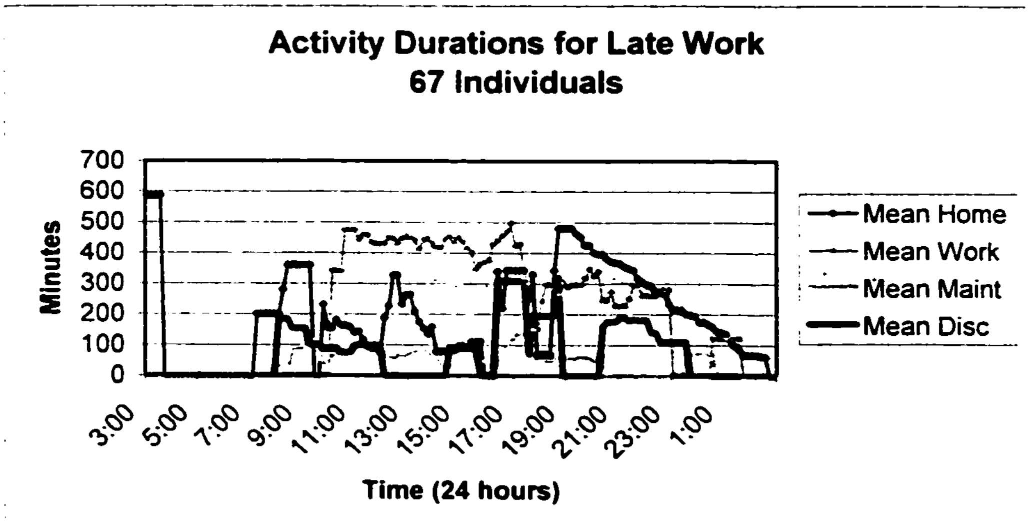

Figure A.6 Activity Durations for Late Work

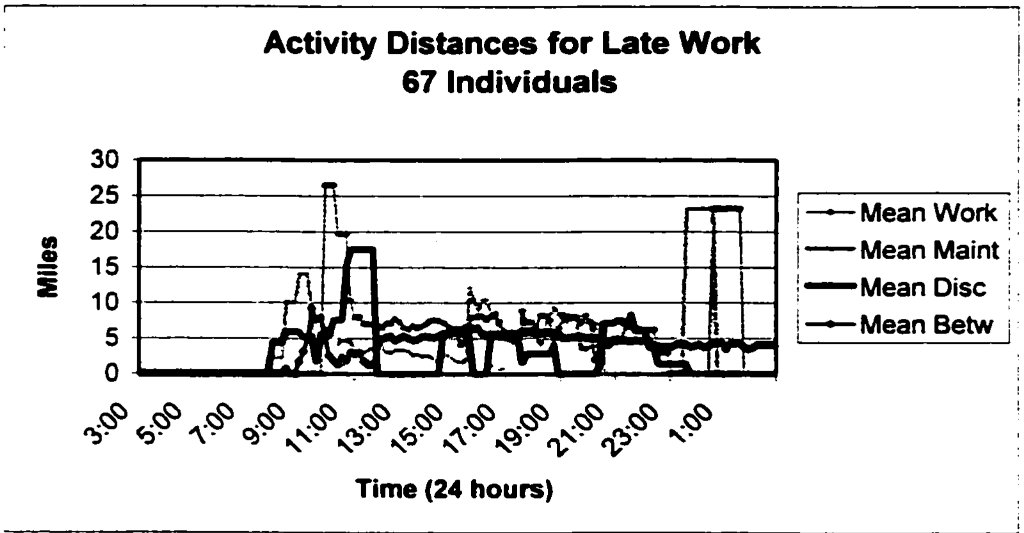

Figure A.7 Activity Distances for Late Work

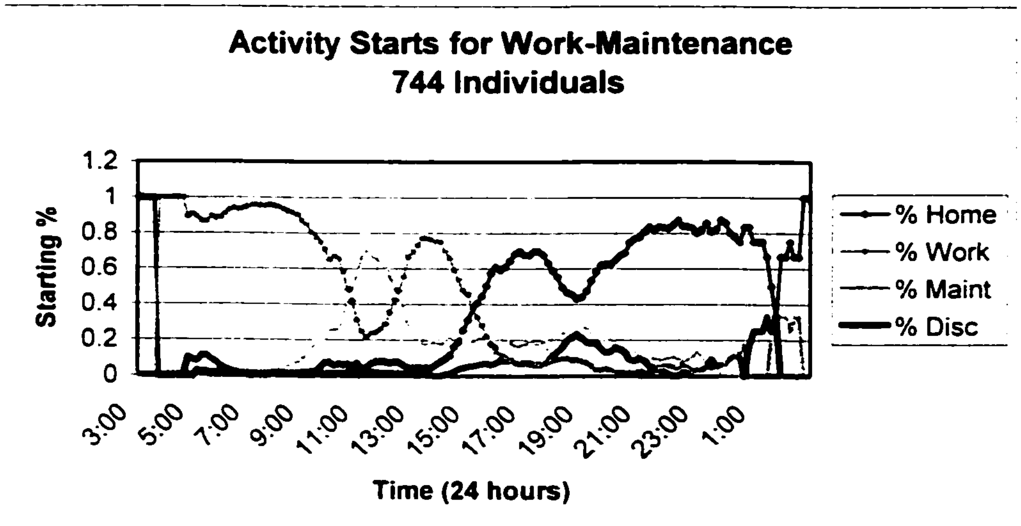

Figure A.8 Activity Starts for Work-Maintenance

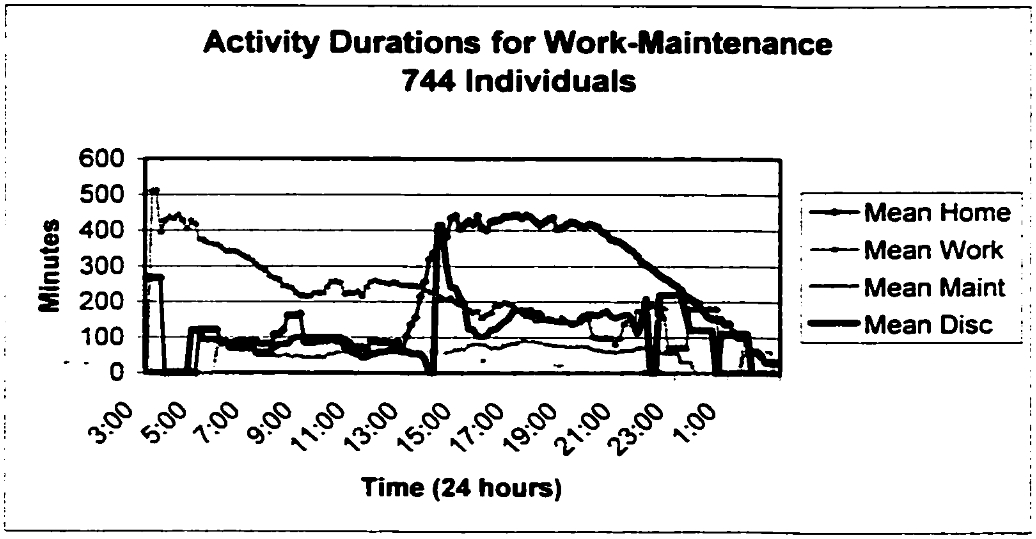

Figure A.9 Activity Durations for Work-Maintenance

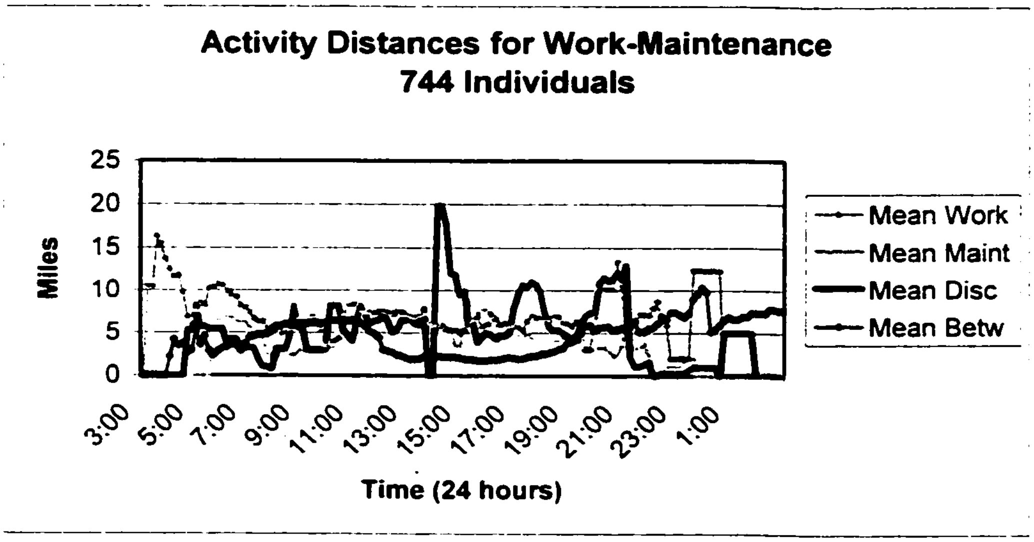

Figure A.10 Activity Distances for Work-Maintenance

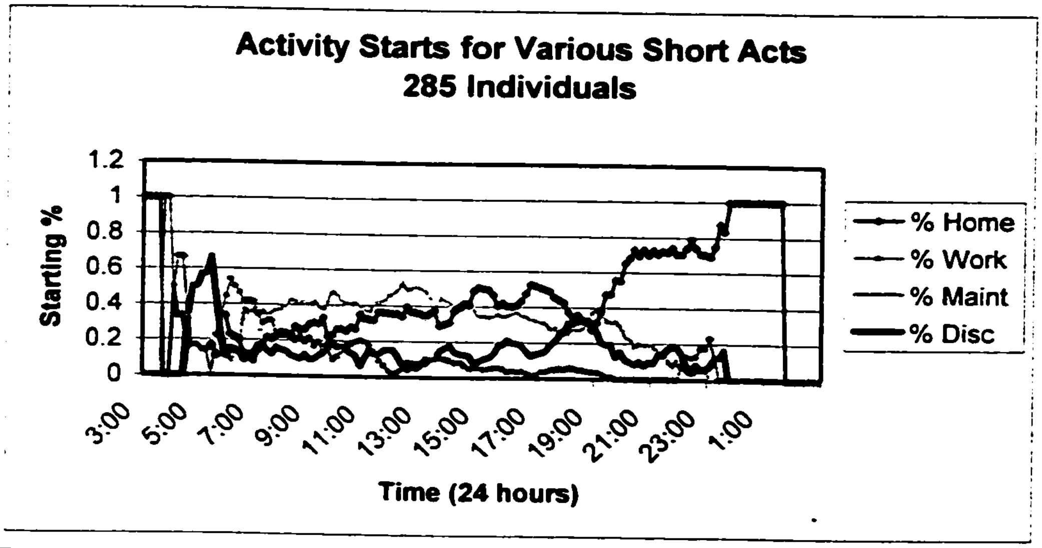

Figure A.11 Activity Starts for Various Short Activities

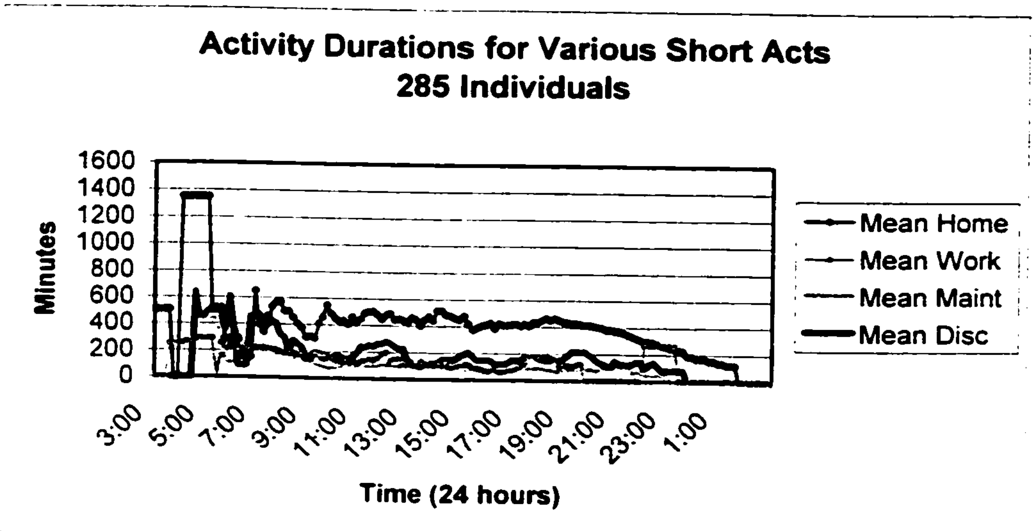

Figure A.12 Activity Durations for Various Short Activities

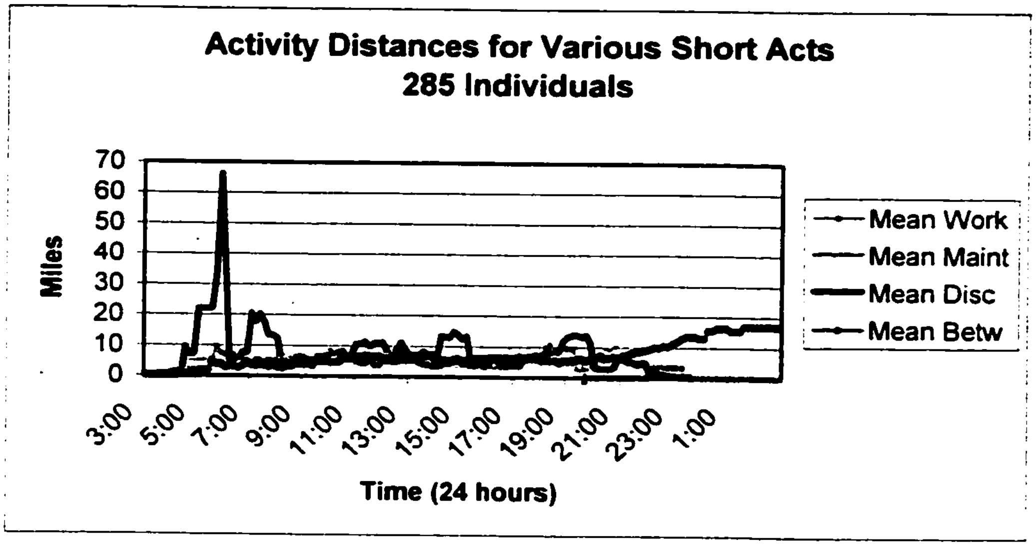

Figure A.13 Activity Distances for Various Short Activities

APPENDIX B

DISTRIBUTIONS OF ALL ADULTS NOT WORKING FULL TIME

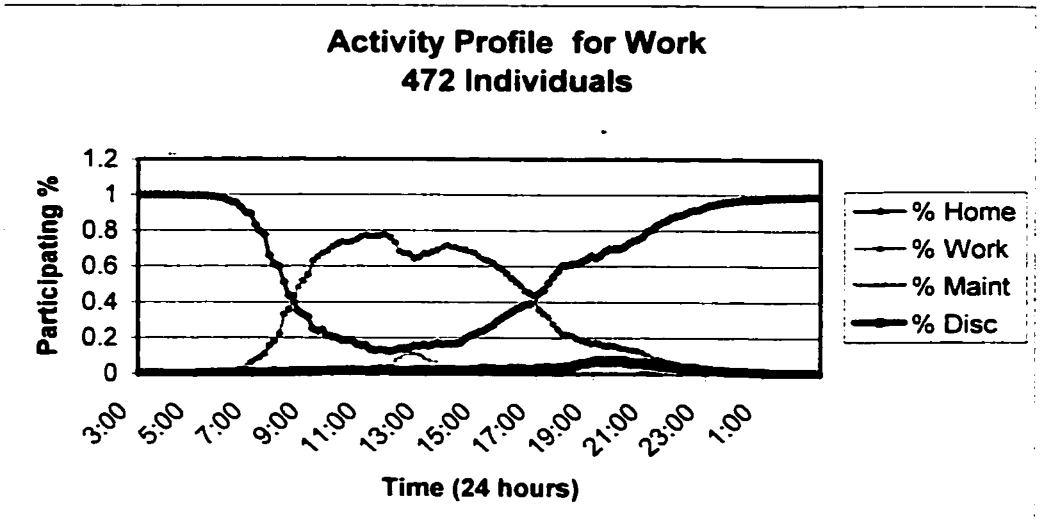

Figure B.1 Activity Profile for Work

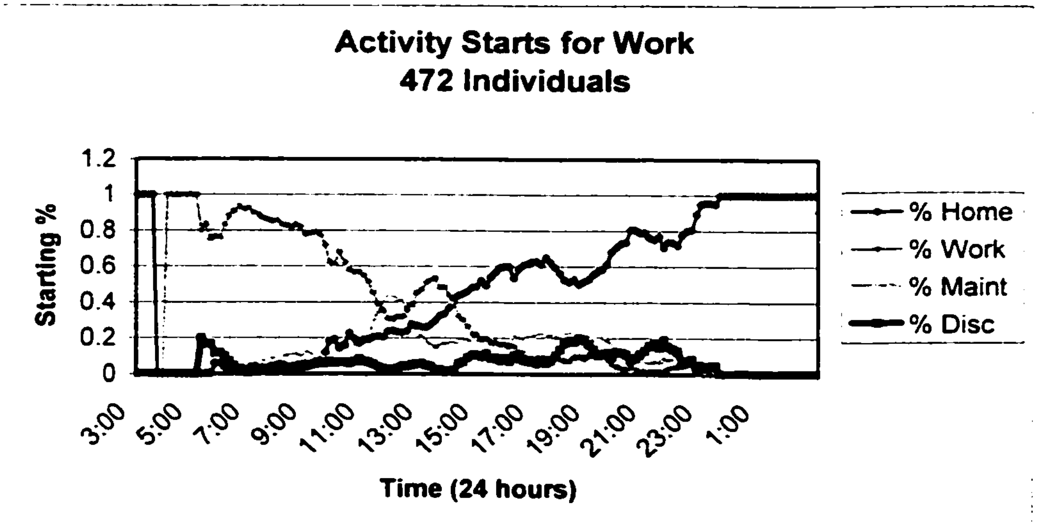

Figure B.2 Activity Starts for Work

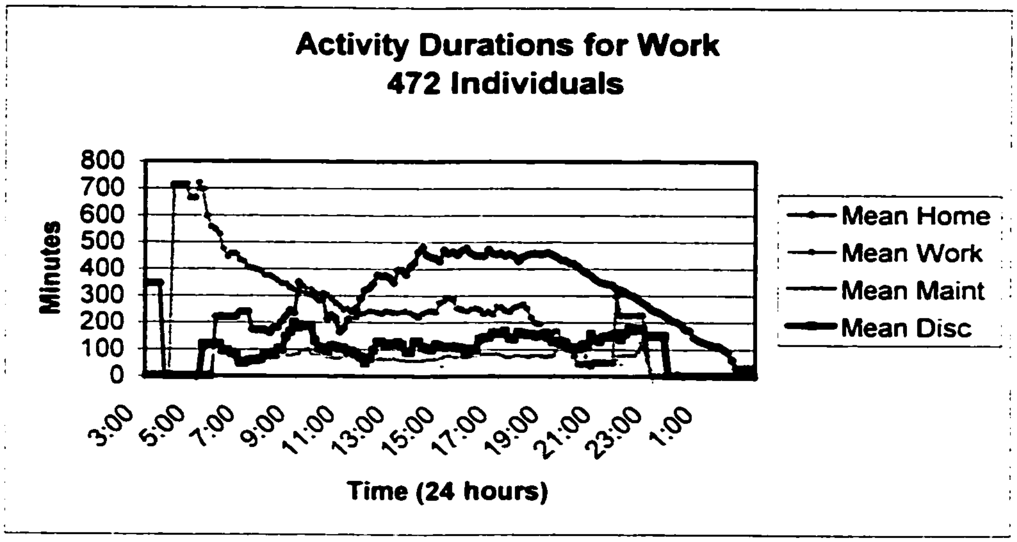

Figure B.3 Activity Durations for Work

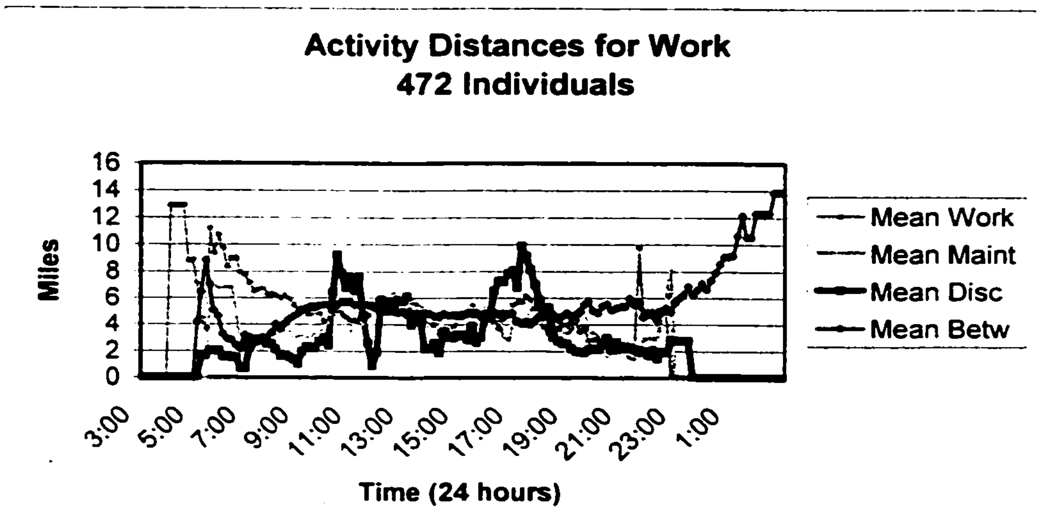

Figure B.4 Activity Distances for Work

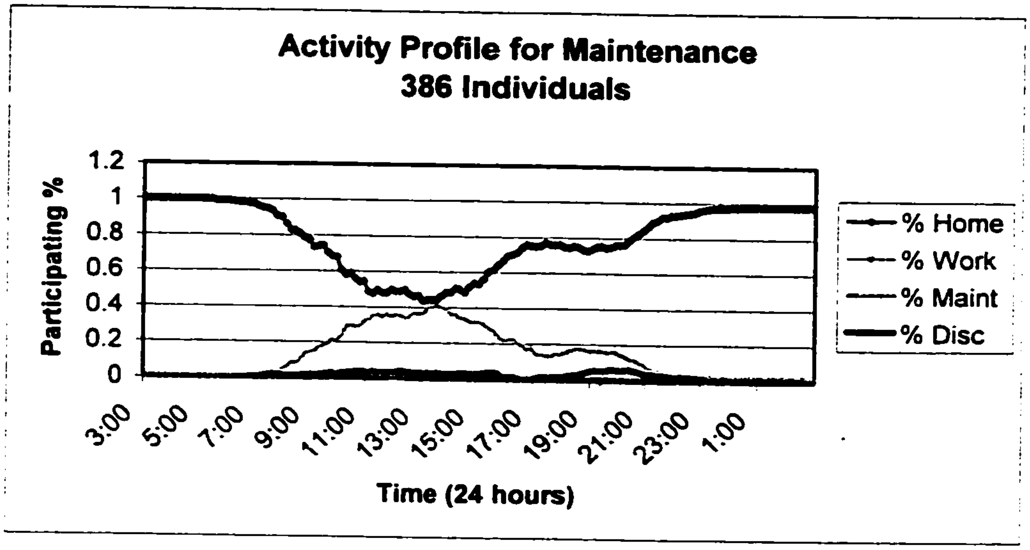

Figure B.5 Activity Profile for Maintenance

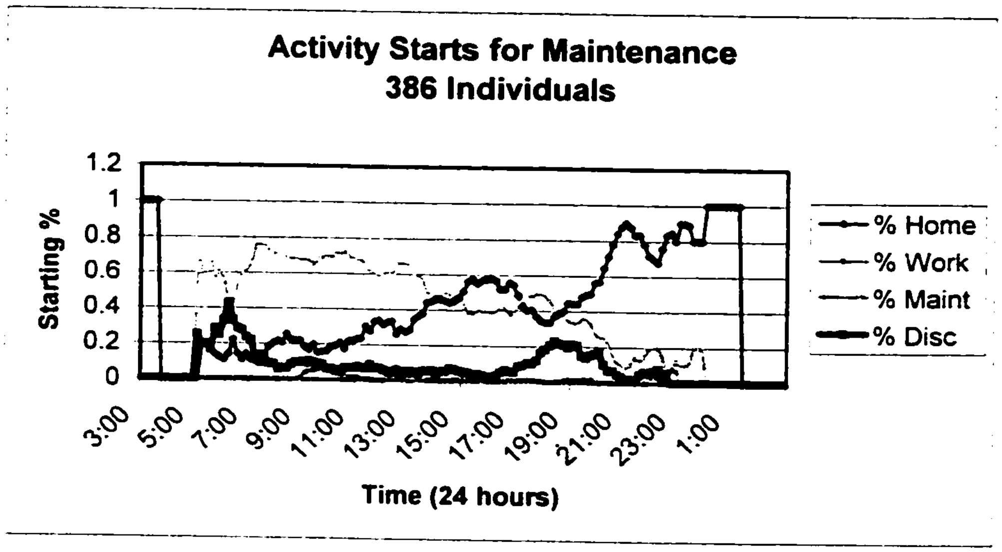

Figure B.6 Activity Starts for Maintenance

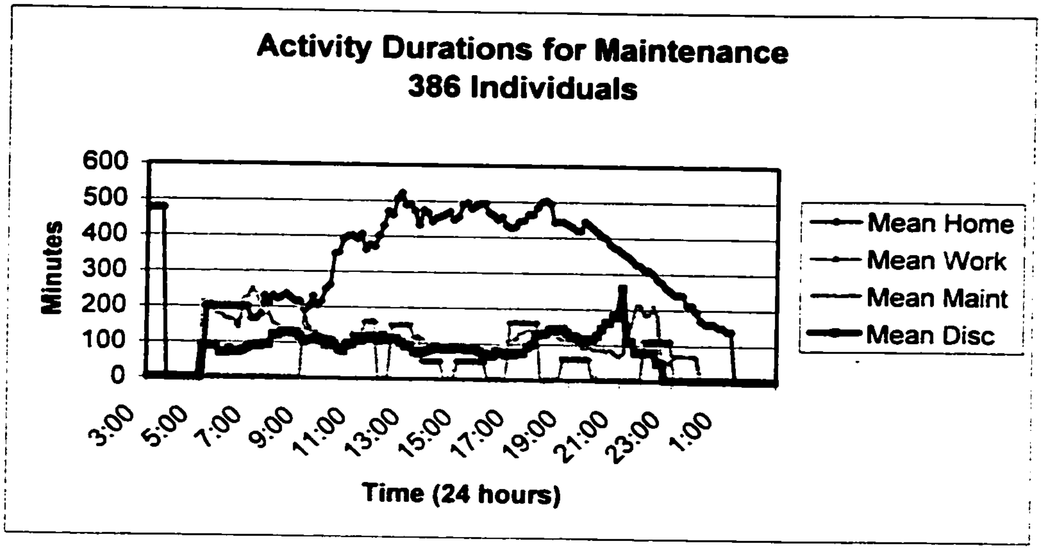

Figure B.7 Activity Durations for Maintenance

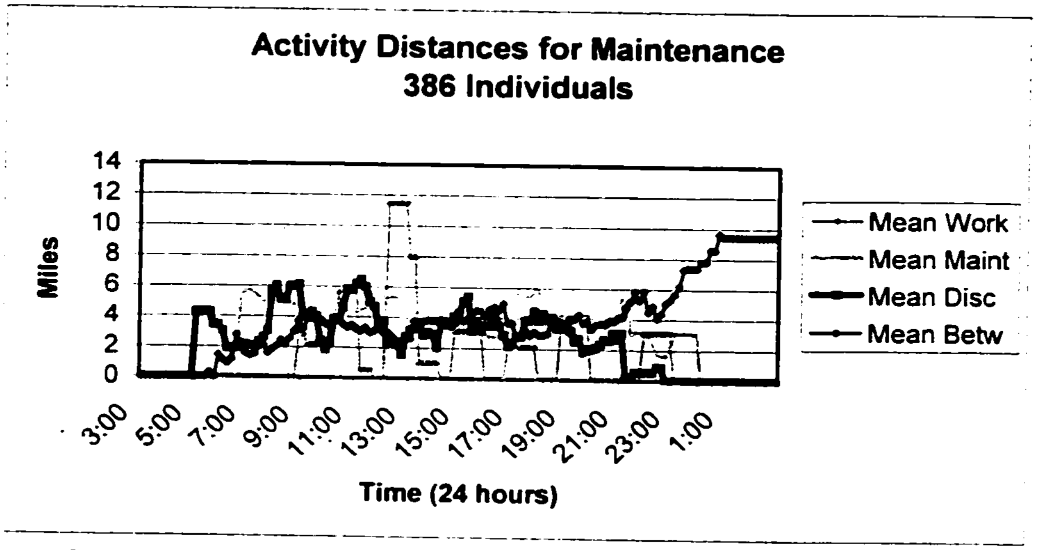

Figure B.8 Activity Distances for Maintenance

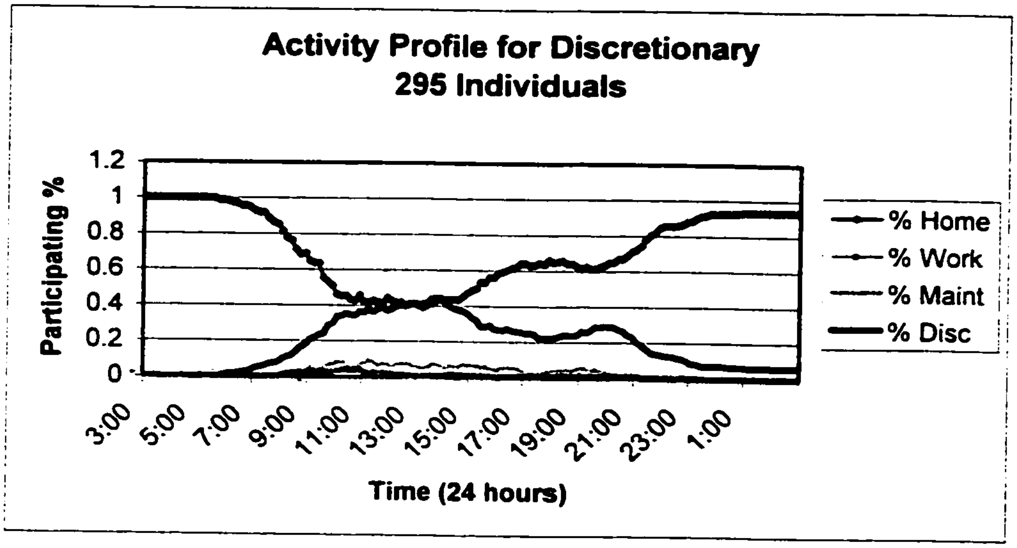

Figure B.9 Activity Profile for Discretionary

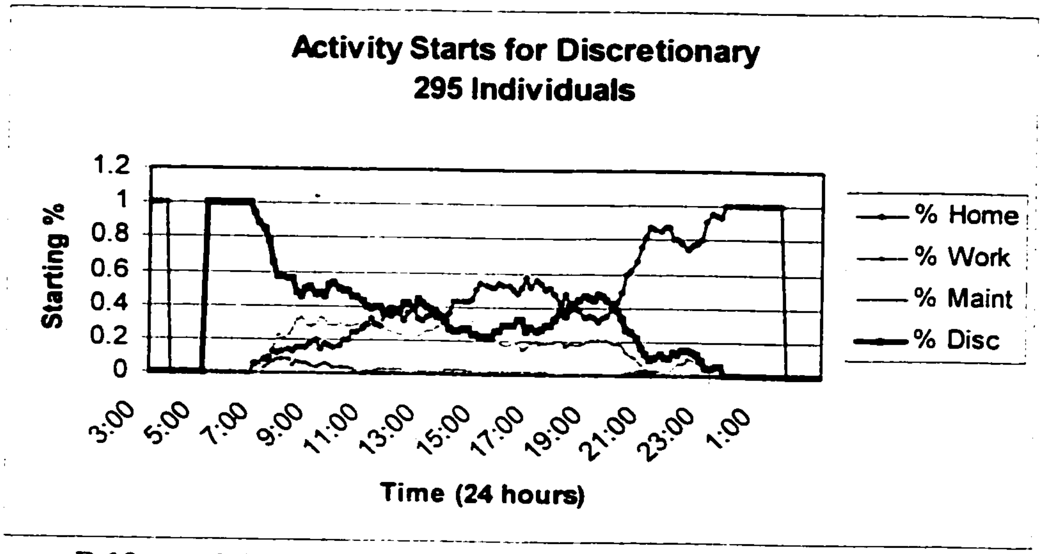

Figure B.10 Activity Starts for Discretionary

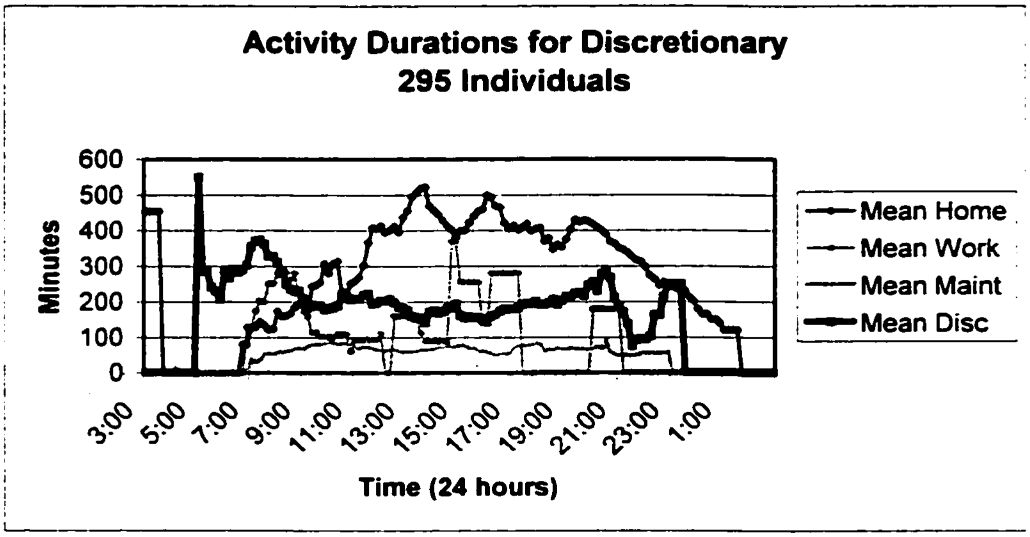

Figure B.11 Activity Durations for Discretionary

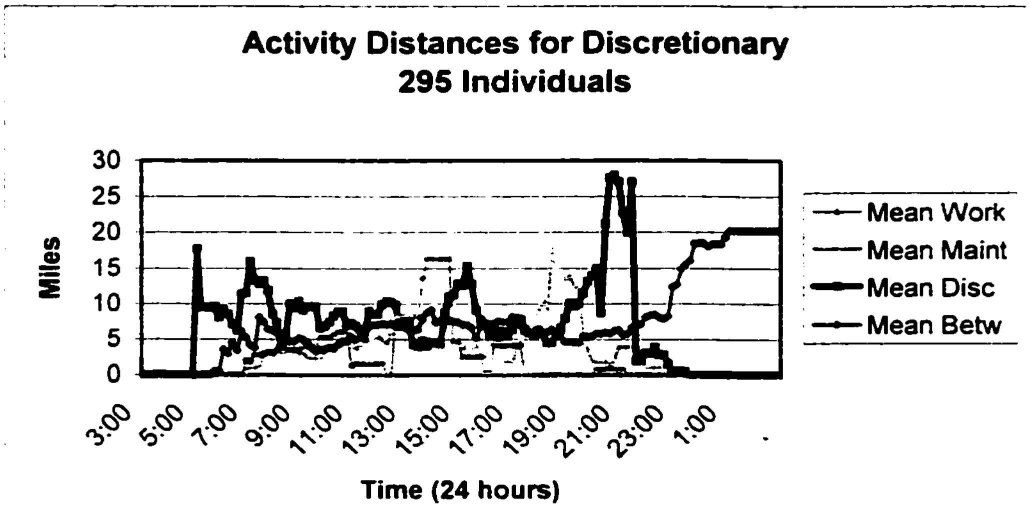

Figure B.12 Activity Distances for Discretionary

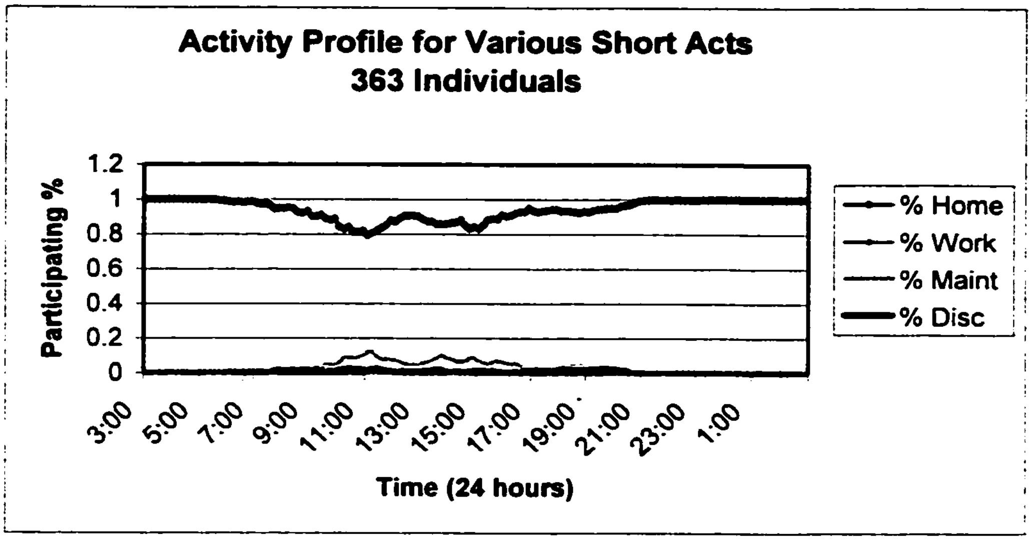

Figure B.13 Activity Profile for Various Short Activities

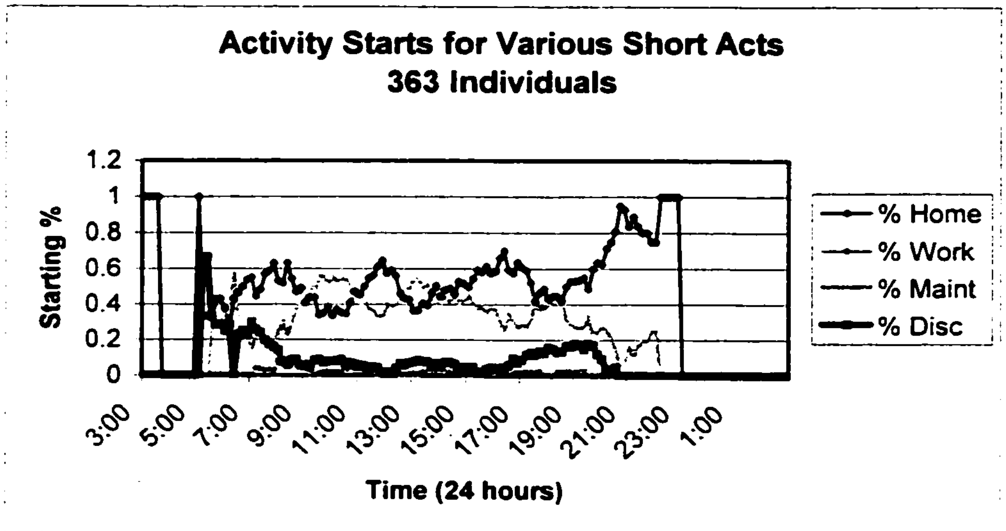

Figure B.14 Activity Starts for Various Short Activities

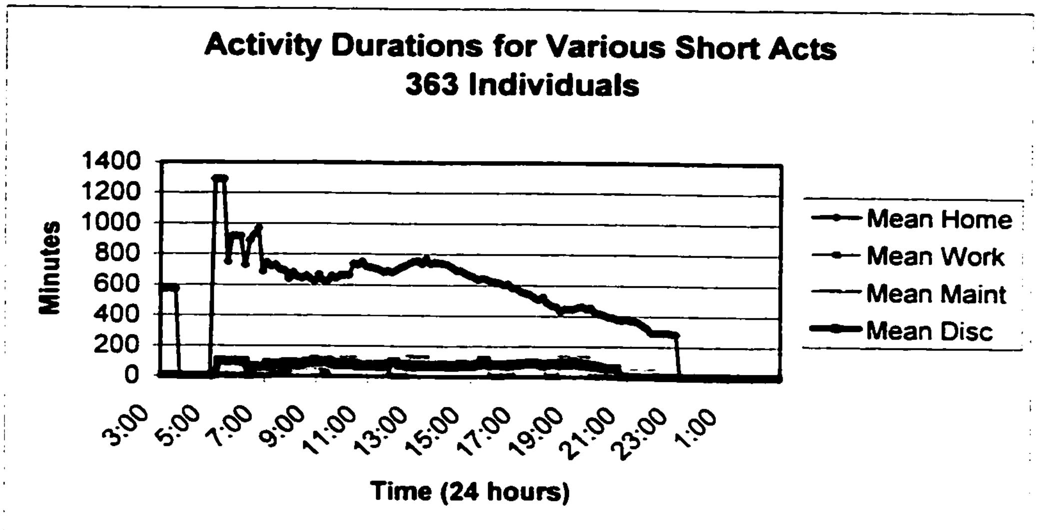

Figure B.15 Activity Durations for Various Short Activities

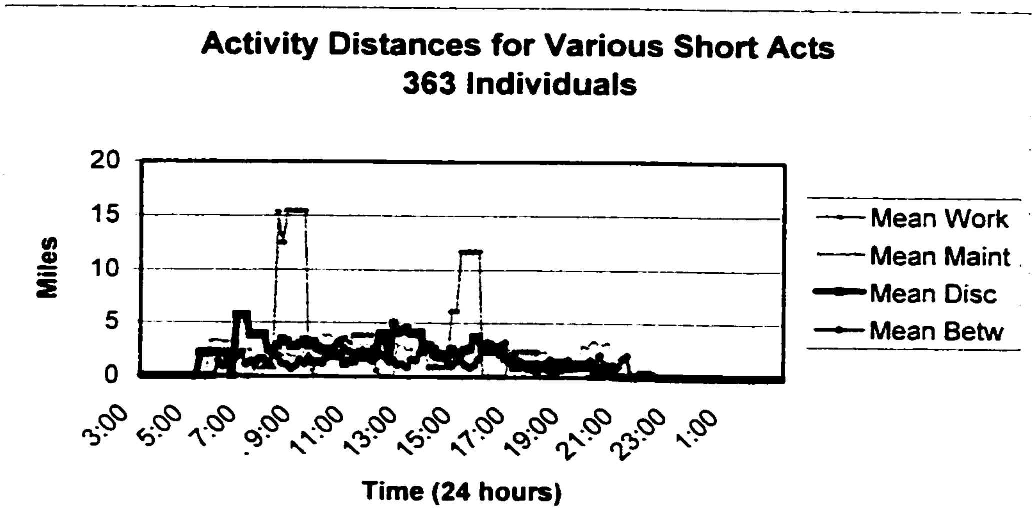

Figure B.16 Activity Distances for Various Short Activities