Agent-based Dynamic Activity Planning and Travel Scheduling Model:

Data Collection and Model Development

BY

JOSHUA A. AULD
B.S., University of Illinois at Urbana-Champaign, 2002
M.S., University of Illinois at Chicago, 2007

THESIS

Submitted as partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Civil Engineering
in the Graduate College of the University of Illinois at Chicago, 2011

Chicago, Illinois

DEDICATION

This work is dedicated to my wife, Gabriela, and sons Joshua and Charlie. Without their encouragement its completion would not have been possible.

ACKNOWLEDGEMENT

I would first like to thank my primary advisor, Dr. Kouros Mohammadian, for his unwavering support and guidance through the process of completing this work. I would also like to thank my thesis committee—Dr. Peter Nelson, Dr. Eric Miller, Dr. Sean Doherty and Dr. Jane Lin -- for their encouragement and assistance. They provided advice and guidance in many ways throughout this process. I would also like to thank the many colleagues and friends who made important contributions to the completion of this work at various points including, Dr. Taha Rashidi, Dr. Chad Williams, Mahmoud Javanmardi, Dr. Amir Samimi and Martina Frignani, as well as the undergraduate students who assisted in the data collection process. In addition, the contributions of Dr. Matthew Roorda in helping to develop the activity scheduler and Dr. Sean Doherty and Dr. Martin Lee-Gosseling for providing access to critical behavioral data are also gratefully acknowledged. I am also grateful to Dr. Kermit Wies and Matthew Stratton at the Chicago Metropolitan Agency for Planning for all of their help and support. The National Science Foundation IGERT Program, Chicago Metropolitan Agency for Planning and the Illinois Center for Transportation have all provided funding at various points during the completion of this work for which I am grateful. I would also like to acknowledge all of the reviewers, anonymous and otherwise, who took the time to provide comments and advice on all aspects of this work at various points. Finally, I would like to thank all of my family and friends for their continuing support and encouragement throughout my academic career.

AUTHORS NOTE

I would like to thank Martina Frignani and Dr. Taha Rashidi for allowing the inclusion in this thesis of work first published as, respectively:

Frignani, M., J.A. Auld, A. Mohammadian, C. Williams and P. Nelson (2010). Urban Travel Route and Activity Choice Survey (UTRACS): An Internet-Based Prompted Recall Activity Travel Survey using GPS Data. Transportation Research Record: Journal of the Transportation Research Board, 2183, 19-28.

Auld, J.A., T. Rashidi, M. Javanmardi and A. Mohammadian (2011). Activity Generation Model Using a Competing Hazard Formulation. Forthcoming in Transportation Research Record: Journal of the Transportation Research Board.

In addition, portions of this work have previously been published in various research journals which are gratefully acknowledged. Included in these are articles published as:

Auld, J.A. and A. Mohammadian (2011). Constrained Destination Choice in the ADAPTS Activity-Based Model. Forthcoming in Transportation Research Record: Journal of the Transportation Research Board.

Auld, J.A. and A. Mohammadian (2010). An Efficient Methodology for Generating Synthetic Populations with Multiple Control Levels. Transportation Research Record: Journal of the Transportation Research Board, 2175, 138-147.

Auld, J.A., A. Mohammadian and M.J. Roorda (2009). Implementation of a Scheduling Conflict Resolution Model in an Activity Scheduling System. Transportation Research Record: Journal of the Transportation Research Board. 2135, 96-105.

Auld, J.A. and A. Mohammadian (2009). Framework for the Development of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) Model. Transportation Letters, International Journal of Transportation Research, 1 (3), 245-255.

Auld, J.A., A. Mohammadian and S.T. Doherty (2009). Modeling Activity Conflict Resolution Strategies Using Scheduling Process Data. Transportation Research Part A: Policy and Practice, 43 (4), 386-400.

Auld, J. A., C. Williams, A. Mohammadian and P. Nelson (2009). An Automated GPS-Based Prompted Recall Survey with Learning Algorithms. Transportation Letters, International Journal of Transportation Research, 1 (1), 59-79.

TABLE OF CONTENTS

TABLE OF CONTENTS (continued)

TABLE OF CONTENTS (contınued)

LIST OF TABLES

LIST OF TABLES (continued)

LIST OF FIGURES

LIST OF FIGURES (continued)

NOMENCLATURE

AADT	Annual Average Daily Traffic
AAPD	Average Absolute Percent Difference
ACS	American Community Survey
ADAPTS	Agent-based Dynamic Activity Planning and Travel Scheduling
ALBATROSS	A Learning-BAsed TRansportation Oriented Simulation System
AURORA	Agent for Utility-driven Rescheduling Of Routinized Activities
BPR	Bureau of Public Roads
CEMDAP	Comprehensive Econometric Model for Daily Activity Patterns
CHAID	Chi-squared Automatic Influence Detection
CHASE	Computerized Household Activity Schedule Elicitor
CMAP	Chicago Metropolitan Agency for Planning
CPM	Computational Process Model
DTA	Dynamic Traffic Assignment
FAMOS	Florida Activity MObility Simulator
FEATHERS	Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS
GPS	Global Positioning System
ICT	Information and Communication Technologies
IGERT	Integrative Graduate Education Research Traineeship
IID	Independent and Identically Distributed
IPF	Iterative Proportional Fitting
ISTEA	Intermodal Surface Transportation Efficiency Act
ITS	Intelligent Transportation Systems
LOS	Level-of-Service
LL	Log-Likelihood
MAPE	Mean Absolute Percent Error
ML	Mixed Logit
MNL	Multinomial Logit
MORPC	Mid-Ohio Regional Planning Commission
MVOP	Multivariate Ordered Probit
NOx	Nitrogen Oxides
NTS	National Transportation Statistics
O-D	Origin-Destination
PCATS	Prism Constrained Activity-Travel Simulator
PUMA	Public Use Microdata Area
RMSE	Root Mean Squared Error
SAFETEA-LU	Safe, Accountable, Flexible, Efficient, Transportation for Equity Act: A Legacy for Users
SAR	Spatial Autoregressive
SUR	Seemingly Unrelated Regression
TASHA	Travel Activity Scheduler for Household Agents
TAZ	Traffic Analysis Zone
TEA21	Transportation Equity Act for the 21st Century
TRANSIMS	TRansportation ANalysis and SIMulation System
UTRACS	Urban Travel Route and Activity Choice Survey
VDF	Volume-Delay Function
VMT	Vehicle Miles Travelled
VOC	Volatile Organic Compounds
WAAPD	Weighted Absolute Average Percent Difference

SUMMARY

The research detailed in this thesis focuses on the creation of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) travel demand microsimulation model for use in policy analysis, and on the collection of new activity planning data to help in the development of the model. The model is developed as an agent-based microsimulation model which creates travel patterns for each individual in the modeled region under the activity-based modeling framework, which is combined with a disaggregate travel simulator. As such, the model is both a microsimulation of travel demand as well as a microsimulation of route selection, as opposed to the traditional method of developing travel demand using aggregated zonal flows.

The focus of the model is on representing the activity planning and scheduling process as a dynamic process which occurs simultaneously with activity travel simulation, rather than a fixed process standing apart from the rest of the model. The ADAPTS model extends the concept of activity planning horizon to the individual attributes of the activity and uses these horizons to simulate the activity planning episodes in the overall planning framework. Therefore, the model explicitly represents the dynamics of the activity planning and scheduling process, rather than modeling the observed activity-travel patterns as is currently done in most models. In order to simulate the planning process a new planning-order model was estimated which determines at what time and in what order each activity attribute was planned. The use of flexible planning orders requires a new set of models for the attribute choices leading to the creation of "planning-constrained" choice models. The planning constrained destination choice model was estimated from recent survey data and implemented in the ADAPTS simulation model, to demonstrate the concept. The ADAPTS model was then combined with a new incremental simulated dynamic traffic assignment procedure which allowed direct integration between the network simulation and activity-planning process.

A new GPS-based travel survey was developed and implemented in order to capture data to allow the modeling of the activity planning dynamics. The Urban Travel Route and Activity Choice Survey (UTRACS) was an internet-based prompted recall survey which utilized personal GPS-based data collection. The GPS data was used to generate the prompted recall survey and reduce the respondent burden so that the individuals would have more time to answer questions regarding the activity-travel planning process, including plan horizon and flexibility

characteristics regarding the activities and their attributes. The survey was implemented in the Chicago region for a sample of 100 households for a period of two-weeks, providing much of the data used in the ADAPTS model development.

The ADAPTS model components were then implemented in an integrated simulation environment and used to model travel demand for the Chicago region. The model was found to compare favorably to the existing regional travel demand model and observed traffic counts, and provides a wealth of additional data on activity engagement, tour formation, and provides network volumes at detailed time representations. The model validates well, and with additional improvement, will allow for a much wider range of advanced transportation demand management and environmental mitigation policies to be evaluated, as compared to current models.

1. INTRODUCTION

Transportation is a fundamental human activity, which connects individuals to their places of work, friends and relatives, and activity opportunities. It is therefore something that almost everyone experiences on a daily basis and, especially for commuters, can occupy a significant portion of each day. Transportation is one of the most important sectors of the U.S. economy and consumes a significant total of the gross domestic product through fuel usage, road construction, maintenance costs and lost productive time due to congestion. Additionally, the importance of the transportation sector continues to grow as population increases, urban sprawl intensifies, and the demand for transportation continues to grow at a rapid pace. This growth in the transportation sector has had great economic, social and environmental impacts.

The rapidly growing demand for transportation causes significant economic and social problems within the transportation sector and for society in general. Most of these problems are caused by the growth in demand for transportation outpacing the supply. The National Transportation Statistics show that the number of highway vehicle miles traveled (VMT) has grown at an average annual rate of 3.2% since 1960 from around 720 billion in 1960 to almost 3 trillion in 2005 (NTS Table 1-32, 2006). During the same time frame, the total lane miles of roadway has only increased at a 0.3% annual rate from 3.5 million to around 4.0 million miles (NTS Table 1-1, 2006). Taken together, these numbers show a 269% increase in vehicle miles traveled per mile of highway in that time period, which is a significant indicator of increasing density on the nation's roadways. The impacts of this increase are evident in the growth of the congestion problem in most major urban areas. According to the Texas Transportation Institute's urban mobility report, congestion effects in 85 urban areas for the year 2003 included 3.7 billion hours lost to delay, which wasted a total of 2.3 billion gallons of fuel. The total estimated cost of these congestion delays was over $63 billion dollars. These effects have in fact been getting worse over time, with delay hours increasing from 0.7 billion in 1983 to the 3.7 billion hours in 2003 (Schrank and Lomax 2005). This shows that the current solutions, including constructing new lane miles, adding transit routes and implementing intelligent transportation systems (ITS) solutions are not enough to correct the problems caused by congestion.

In addition to congestion effects, there has also been a growing concern with air quality degradation due to the emission of air pollutants such as carbon dioxide, nitrogen oxides (NOx), volatile organic compounds (VOCs) and particulate matter. Air pollution has been recognized as a major threat to public health and to the quality of life. The wide-ranging and complex nature of pollution costs makes it difficult to quantify the overall effect on society, but yearly costs have been estimated to be in the tens of billions of dollars in increased healthcare spending and premature mortality alone. A large portion of total air pollution is derived from human activity. Man-made pollution is generally divided into two types: stationary and mobile source emissions. Stationary source emissions come from both industrial sources such as manufacturing plants and power plants and residential burning for cooking and heating etc., while mobile source emissions are generated by vehicles such as automobiles, airplanes, trains, etc. and non-road engines such as construction machines. The transportation sector is one of the largest sources for many types of air pollution. When the decline in air quality and increased congestion became national issues, it was apparent that in order to improve the situation, changes in the transportation sector needed to be made.

To effect these changes, Congress passed a series of laws, beginning with the Clean Air Act passed in 1963 and amended in 1966, 1970, 1977 and 1990, and enhanced through various transportation appropriations bills like the Intermodal Surface Transportation Efficiency Act (ISTEA), the Transportation Equity Act for the 21st Century (TEA21) and the Safe, Accountable, Flexible, Efficient, Transportation for Equity Act: A Legacy for Users (SAFETEA-LU). These laws and the focus they have placed on advanced transportation demand mitigation strategies and air quality regulatory compliance has greatly increased the need for new models and other techniques that allowed states to analyze the costs, benefits and impacts of these strategies.

This changing focus in transportation planning has led to many improvements in the travel demand models used for planning and forecasting purposes. However, many of the models currently in use are unable to represent the implementation of newly developed and more advanced transportation mitigation strategies because they act only on aggregated vehicle travel flows and do not contain a strong behavioral component for individuals' travel making behavior and their responses to policy changes. There is a need, therefore, for models which explicitly represent the underlying dynamic activity planning and scheduling processes, especially as more and more mitigation strategies are likely to directly impact how individuals plan and schedule their activities. There is also the potential for change in individual planning and scheduling behavior through the growing use and availability of information and communication technologies (ICT). These technologies, such as smartphones, in-car navigation devices and proposed devices such as the Intelligent Traveler Assistant (Dillenburg et al, 2002) among others, can aid individuals in planning and routing and fundamentally change activity-travel patterns.

This thesis discusses the development of a new activity-based model, the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model which incorporates dynamic activity planning by treating each planning or scheduling step which individuals undergo during the creation of their activity travel patterns as an actual event within the overall simulation. First a review of previous work in travel demand modeling, especially focusing on activity-based modeling, is discussed. Research gaps and the contributions of this work are then introduced in light of previous work reviewed. Next, Part I of the thesis introduces the framework for the model development, the completed components of the ADAPTS model, the implementation of a baseline ADAPTS model for the Chicago region, and directions for future work regarding dynamic activity-based travel demand models. Finally, Part II discusses the development of a new GPS-based prompted recall travel survey which serves as the primary source of data for the development of many of the dynamic activity planning behavior model components discussed in Part I. The results of an initial implementation of the survey undertaken in the Chicago region are then presented. Finally, potential improvements and new uses for survey data of this type are discussed in light of the data needs for a model such as ADAPTS.

2. REVIEW OF TRAVEL DEMAND MODELING

2.1. Traditional Travel Demand Models

The traditional approach to estimating travel demand and therefore determining congestion, environmental and other impacts of the transportation system, has been to develop what is known as a four-step travel demand model. In this type of model, travel demand is modeled sequentially with the number of trips from and to each area determined first, followed by the distribution of those trips between all of the areas and the modes and routes chosen for the trips. The traditional four-step model has often been criticized for a variety of shortcomings, including a lack of transferability, poor treatment of time of day characteristics, the independence of each trip made by an individual from their other trips, and the lack of a behavioral component to trip making due to the use of highly aggregated data (Boyce 2002, Kitamura 1996). These models originated in the 1950s and for the most part have not changed much since, except for the addition of feedback loops between the traffic assignment results and the cost input to the gravity modeling stage, which attempts to simulate congestion effects (Boyce 2002).

The most important limitation that the four-step model has in analyzing current transportation demand strategies is its lack of a behavioral focus and the independence of each individual trip. The other deficiencies of the model can be overcome to a certain extent through the use of time-of-day separated O-D matrices, feedback loops and other strategies. However, the independence of individual trips and lack of individual behavior representation present problems that are difficult to overcome, especially when it is desired to forecast responses to complex policies relating to ITS or Travel Demand Management (Kitamura 1996). An example of this would be a transportation demand strategy that encourages workers to telecommute instead of working at an office. The traditional four step model would show a reduction in overall trips, since the work trip would be eliminated. However, in actual practice, it is observed that in-home workers tend to increase their total number of discretionary trips as compared to commuters. Similar results are observed with programs that encourage transit ridership, where trips that were previously completed on the way home from work now generate an entirely separate tour, i.e. the home-work-shopping-home trip tour becomes home-work-home-shopping tour (Bowman and Ben-Akiva 1996). In both cases the use of a transportation demand mitigation strategy caused an overestimate in the reduction of trips in the four-step model because responses such as trip chaining and rescheduling behavior were not considered.

2.2. Activity-Based Modeling of Travel Demand

In order to correct these deficiencies observed in the traditional four-step model, activity-based modeling was proposed. The theory of activity-based modeling states that travel is derived from individuals' participation in activities, and that the participation in activities is driven by fundamental human needs or desires, including basic needs like food, shelter, clothing, and more complex requirements such as socialization, education, recreation, etc (Ettema and Timmermans 1997). The decision to participate in activities, and therefore travel, is based on basic human needs, but these needs can vary due to many factors, including personal characteristics, household composition, and the availability of opportunities to satisfy those needs. Additionally, the ability of an individual to participate in activities is constrained. Several types of constraints were identified by Hagerstrand in his work on time geography (Hagerstrand 1970). These constraints include capability constraints, referring to the physical limitations on human activity and coupling constraints, where an individual's ability to participate in activities is limited by the requirement that they either need to participate in an activity with another individual or share a resource with another individual at a specific time. Hagerstrand used these constraints to develop a space-time prism that included all feasible activity patterns.

Attempts have been made to relate the activity types to broad project categories, which cover the basic needs of individuals as an organizing principle (Miller 2005). This allows provisional schedules for each project, called the project agendas, to be created in advance, and then actual schedules could be created from the provisional schedules within each project, which would better represent people's actual scheduling processes. The combination of all of the institutional constraints, such as store hours, work schedules and others, with the household constraints including joint activities, child care and maintenance needs, and the resource and space-time constraints, determines how an individual is able to schedule activities to satisfy their needs.

If the full range of human activities is included, then theoretically the model should specify all passenger travel, and would allow for a very accurate and complete estimation of regional travel demand. These models, when combined with a regional microsimulation framework, essentially replace the trip production and distribution stage of the traditional model. The aggregated zonal flows are instead derived by summing the individual travel episodes that come out of each activity pattern (Bowman and Ben-Akiva 1996). However, difficulties have arisen in operationalizing models of this type due to the complexity of human problem solving and decision processes. As a result of this, two general themes or model types have developed within the broader set of activity-based modeling. These include models which use econometric or utility-maximizing approaches to approximate decision-making behavior, and models which attempt to represent the actual cognitive process of decision making in the schedule formation process (Ettema and Timmermans 1997).

2.3. Econometric Activity-Based Modeling

Econometric models make use of utility maximization theory to determine the scheduling choices that individuals make. These models usually use a logit or nested logit model to represent the decision-making processes. A large portion of the work that has been done on activity-based modeling has occurred with these types of econometric models. Well known models of this type include the Bowman and Ben-Akiva (2001) model, the CEMDAP model (Bhat et al. 2004), MORPC model (Vovsha and Bradley 2004) and Jakarta model (Yagi and Mohammadian, 2008).

Most of the econometric-based models consider daily activity and travel patterns to be comprised of a set of tours (Bowman and Ben-Akiva 2001, Vovsha and Bradley 2004). The tours are defined as a series of travel and activity episodes which originate and terminate at the home-location. The tours are generally grouped into primary and secondary tours, with the primary tour including what is considered the highest priority activity of the day, and all other scheduled tours are considered secondary tours. For an employed individual or student the primary tour generally contains a work or school episode, whereas the secondary tours generally contain maintenance or leisure activities (Wen and Koppelman 2000).

To construct the tours, most econometric models make use of the concept of activity priority, based on the purpose of the activity. Work or school activities have the highest priority, followed by maintenance and discretionary activities (Vovsha and Bradley 2004). In some models, such as the MORPC model, the priority is also determined by the degree of interpersonal fixity and the duration of the activity, with longer activities and those with other people considered to be higher priority.

The tour-based structure is adopted by these models to reduce the choice set within the nested-logit structure, as the creation of an activity-travel pattern where the activities are not grouped into tours can be considered a combinatorial problem (Ettema and Timmermans 1997). In order to reduce this complexity, pre-defined tour sequences are adopted, such as home-work-home or home-maintenance-work-home, and the models are specified as a nested series of choice models. For example, in the model by Wen and Koppelman (2000), the model first generates the number of household maintenance stops for the day, assigns them to adult household members, and finally allocates vehicles to each adult household member, where each subsequent choice is conditional on the previous one. After this is completed, the tour structure is then created by first choosing the number of tours, then determining for each tour if a maintenance stop will be included, and finally choosing from the resulting available tour patterns.

As is evident, models of this type are structured in a highly sequential matter, with the daily-activity pattern chosen at one time. In addition, most of the models only use a limited number of time periods for analysis, for example, morning peak, midday, evening peak and night, or some other division of this type. This is also done to reduce the number of choices in the model, since time of day is an explicit choice made. Therefore, models of this type have been criticized for how they capture time of day effects (Ettema and Timmermans 1997), as well as how they represent the actual scheduling process (Garling et al. 1994) through the sequential structure of the logit model and the all-at-once schedule creation process.

2.4. Rule-Based Activity Scheduling Models

A modeling framework that has been advanced as an alternative to correct some of these deficiencies is the rule-based or computational process model (Garling et al. 1994). Rule-based models tend to use either simple heuristics to approximate the scheduling process (Roorda et al. 2005) or process models which attempt to represent the decision making process itself, rather than modeling only the outcomes of the process as in an econometric model. Much of the theory of the computational process model is based on work by Newell and Simon (1972) in the development of the production system. The production system is a model of cognitive behavior which states that "individuals' choices are based on their cognition of their environment" (Ettema and Timmermans 1997). This means that a cognitive process can be represented by a model which contains an individual's memory, including knowledge of their environment and the results of their interactions with it, rules which operate on that memory and some currently known information about the environment. This allows the individual to form some resulting thought or to take action, the results of which are added to the individual's memory. The rules are usually introduced as a set of if-then rules, where the current information in the system is matched to the conditions of the "if" statement. If a rule is matched the action represented by the associated "then" statement is undertaken, and the results of the action can then be used to update the rules if necessary (Ettema and Timmermans 1997).

Although less research has focused on this area, several models using rule-based frameworks or computational process models have been developed. One of the first models to be developed using the CPM framework was created by Hayes-Roth and Hayes-Roth (1979). The Hayes-Roth model was in fact the first to apply the principles to activity scheduling. More recent models include SCHEDULER (Golledge et al. 1994), ALBATROSS (Arentze et al. 2000), TASHA (Roorda et al. 2005b, and FAMOS (Pendyala et al. 2004). These models all attempt, in some way, to specify the process of activity scheduling, and are therefore potentially more theoretically satisfying as well as more policy sensitive, since this type of model is the only one which would represent policy scenarios which actually represent changes in the scheduling process itself.

2.4.1 SCHEDULER

The SCHEDULER model is an early instance of the use of a computational process model in activity scheduling, which updates the earlier Hayes-Roth model to correct certain deficiencies in the decision making process (Golledge et al. 1994). It attempts to model the learning process by storing the outcomes of each scheduling experience into a long-term memory and uses those outcomes in the following activity scheduling steps. By this process the modeled individual can be said to learn about their environment and use the knowledge gained to make more informed decisions as the model progresses. The individual's long-term memory is represented using the concept of the cognitive map, which contains their imperfect knowledge about the system, i.e. activity locations, travel times and temporal constraints, and is updated through experience (Golledge et al. 1994).

In the SCHEDULER model, it is assumed that there is a list of prioritized activities that need to be scheduled, which is similar to the concept of the project agenda described earlier. The model then schedules these activities according to the given constraints. For this model, the computational process is represented by the attempts to add activities to the schedule, where the activities are added in the order of highest priority, and if the constraints do not allow the high priority activity to be added, the next highest priority activity is scheduled (Golledge et al. 1994). As such, the CPM used is a simplified version of actual decision making and conflict resolution behavior as it is based solely on the assumed priorities of the activities and available time in the schedule.

2.4.2 TASHA

The TASHA model uses concepts similar to the SCHEDULER system, and was created for travel demand estimation in Toronto, Canada (Roorda et al. 2005a). Unlike the SCHEDULER model, the TASHA model is designed as part of a full microsimulation model. As such, activity generation was considered within the model, while the SCHEDULER model operated on previously defined activity agendas. In the TASHA model, schedules are built by generating activities, inserting activities into project agendas and inserting activities from agendas into schedules. Activities in TASHA are generated according to their observed frequencies in a household travel survey of the area. The activities are generated, along with feasible start times and durations generated from observed joint distributions, and added into the individual project agendas. The model then uses a similar computational process to develop the activity schedule as found in SCHEDULER. Both focus on a priori heuristic rules to fit activities into a schedule. The TASHA scheduler uses a large number of logical rules to generate realistic schedules. The rules relate to how and when activities can be added and how scheduling gaps are filled (Roorda et al. 2005a).

The TASHA model uses a set priority or precedence rule to insert activities from the agenda to the schedule. Priority in this context relates to the utility of the project, while precedence relates to the degree of preplanning and temporal fixity of the activity. However, in this model priority of activities is approximated by their precedence (Roorda et al. 2005b). This means that activities which are observed to be more pre-planned are considered to have higher priority. The priority order used in TASHA assumes that work activities are highest priority, followed by school, then joint other and shopping activities and finally individual other and shopping activities. The activities are added to the schedule in this priority order. In addition, since activities are generated randomly, conflict resolution becomes an important part of the model Conflict resolution in TASHA is handled by shortening activities, shifting the activities, doing both or splitting the activity If there is no feasible way to resolve the conflict, the new activity is dropped from the schedule Much like the SCHEDULER model, the cognitive process is represented in TASHA by the scheduling heuristics based on the activity priority and whether it fits into the schedule The TASHA model, however, adds an activity generation component and uses somewhat more realistic scheduling rules

2.4.3 ALBATROSS

Another currently operational rule-based system is the ALBATROSS model, developed to estimate travel demand in the Netherlands (Arentze et al 2000) This model, like the TASHA model, is based on travel survey data Additionally, it uses the concept of the schedule skeleton, which represents the routine activities of the individual In the ALBATROSS model, these routine activities are in fact never changed or modified, and the attributes of these activities, including location, time of day and duration are taken as given Unlike TASHA, however, it uses a complicated series of decision rules to build the complete activity schedule, rather than generating the activities based on their distributions ALBATROSS represents another attempt to create a computational process model of scheduling behavior

The ALBATROSS model is designed as a microsimulation model at the household level for a one day scheduling period It simulates activity scheduling for individuals in a random order, and for scheduling within households uses the other household members' current schedules as input The model begins by first deciding on the mode chosen for the travel to work, which conditions all other decisions in the model Next, the model decides whether or not to add an activity of each pre-defined type to the schedule skeleton, and if the activity is added it chooses the duration and party composition Afterwards, a general time-of-day for each activity is chosen, the activities are linked into tours, modes are assigned to the tours, and locations are chosen for each activity All of these decisions are made sequentially, with the previous choices and spatio-temporal constraints conditioning the following decision Like the other models reviewed, ALBATROSS also assumes a fixed activity priority, and all of the modeling stages follow this priority assumption For example, the decision to add an activity proceeds from high to low priority activities, as does the time-of-day and other attribute choices

All of the decisions in ALBATROSS are made using decision trees to represent the choice process The decision trees meet the conditions for specifying a production system of cognitive behavior (Garling et al 1994), since they represent a mutually exclusive set of condition-action rules The decision making process is followed sequentially in the order listed previously, according to what was felt to be the closest representation of decision making behavior, i e with the mode to work being the most important choice, followed by the addition of flexible activities and specifying their attributes The ALBATROSS model represents an important step in developing a complete model of activity scheduling behavior

2.4.4 PCATS / FAMOS

The PCATS model developed by Kitamura et al (1997) and the FAMOS model derived from it (Pendyala et al 2005) utilized the concept of the space-time prism first proposed by Hagerstrand (1970) to develop the individual activity travel schedules The model starts by setting fixed space time points in the activity schedule based on what were considered fixed activities such as work, school, and others as well as the morning and evening at home activities These activities determined fixed points in the activity-schedules around which the remaining activities were added The fixed points determined where and when individuals had to be at the start and end of each activity, although this constraint is somewhat flexible for the morning and evening at home episodes, and created feasibility constraint for further scheduling In other words, if an individual was to leave home at 9AM and be to work at 10AM, any activity or combination of activities at locations for which the total drive time to each activity plus the duration of the activity plus the drive time from the last activity to the work activity would be feasible The PCATS (and FAMOS) models would then search for these "Prism Constrained" openings in the activity schedules and follow a series of sequential models to generate and plan activities The activity generation model used in PCATS determines if in-home or out of home activities are used to fill the openings and depends on the open prism characteristics such as the amount of time available and the time of day, as well as various household and individual characteristics (Pendyala et al 2004) Activities are continuously generated until the available prisms are filled, with the attributes of each activity planned sequentially after duration In the model, the destination and mode choices are made first using a nested logit model, followed by a hazard-based duration model, which also determines if the activity will use up the remaining available time or if another activity will occur (Pendyala et al

2004). The PCATS and FAMOS model, then, represent a type of simplified rule based model, where the scheduling rules are implemented using simple logit models.

2.5. Models of Activity Scheduling Dynamics

The scheduling process has rarely captured short-term scheduling dynamics as proposed in several conceptual models (Litwin and Miller 2004, Miller 2005). Empirical observations of some of the dynamic aspects of activity scheduling have been conducted (Lee and McNally 2004, Joh et al. 2005, Roorda and Miller 2005, Clark and Doherty 2008, Ruiz and Roorda 2008), and aspects of dynamic activity scheduling such as planning horizons and conflict resolution have been modeled (Mohammadian and Doherty 2005, Lee and McNally 2006, Ruiz and Timmermans 2006, Auld et al. 2008a). Recently, models have even begun to account for short-term adjustment and rescheduling processes, such as the AURORA model (Joh et al. 2002, Joh 2004) and the related FEATHERS model (Arentze et al. 2006). These developments have all been aided greatly through new sources of data describing the scheduling process such as CHASE (Doherty et al. 2004), REACT (Lee and McNally 2001) and others (Ruiz and Timmermans 2006, Zhou and Golledge 2007, Clark and Doherty 2008).

All of the currently operational process models previously discussed necessarily make many simplifying assumptions about the scheduling process itself. These simplifications can include using an assumed priority order of activities to sequence the addition of new activities to the schedule, as in TASHA (Roorda et al. 2005) and others. Another simplification involves using a fixed sequence for planning attributes as in most econometric models, the CEMDAP system (Bhat et al. 2004) and ALBATROSS (Arentze and Timmermans 2000) among many others. In fact, to the best of the author's knowledge, all activity-based modeling systems assume some a priori planning order for specifying the activity attributes. Recent data collection efforts including CHASE (Doherty et al. 2004) and others have shown that priority assumptions are unrealistic. It is likely too that the planning order assumptions typically made also do not reflect the reality of activity scheduling. Analysis of planning time horizons from scheduling process data shows that many activities are opportunistically planned (Mohammadian and Doherty 2005) during the execution of a tour, which could not be handled by scheduling models where the activities are selected first, then formed into tours.

3. RESEARCH GAPS AND CONTRIBUTIONS OF THE WORK

The currently implemented rule-based activity scheduling models that have been reviewed reveal several deficiencies which can be addressed in order to create a more fully realized activity planning and scheduling process simulation. Some of these models, such as the TASHA, ALBATROSS and SCHEDULER, were developed to demonstrate the ability to create daily schedules, but many aspects of the underlying behavioral processes remain unspecified. Areas where further research is needed include the use of behavior process data in activity generation and conflict resolution, the extension to a weeklong scheduling period, moving from static to dynamic activity planning, analyzing the transferability of behavior rules and verifying the accuracy of the models.

The ALBATROSS and TASHA systems represent the most advanced attempts to represent the underlying activity scheduling process in an activity-based model system. However, the scheduling processes in both models were designed without empirical data regarding the actual scheduling process, and many assumptions are made regarding how scheduling is carried out. In other words, the scheduling model in ALBATROSS does not account for processes of rescheduling and conflict resolution. And in both models, activities are generally planned in a fixed order of priority and even the attributes of each individual activity are determined in a predefined, sequential manner. In addition, in each model, the dynamics of the activity-travel pattern are not considered. Each modeling system specifies the activities to be performed and the attributes for each activity separate from the actual execution of those activities. This issue is starting to be addressed, for example by the AURORA model (Joh et al. 2004) which accounts for some rescheduling operations, however much work remains in making activity planning and scheduling fully dynamic. These are important behaviors which need to be included in order for the model to be useful for advanced policy anal ysis. Additionally, all of these models are based on travel diary data alone. Therefore, data sources on the scheduling process itself which have recently become available are not used.

The main contribution of this research will be the addition of the process data to the schedule modeling stage. As previously mentioned, most of the computational process models operate based only on an assumed priority of activities and whether they can be fit into the schedule, along with other ad hoc scheduling rules devised to make a realistic schedule (Roorda et al 2005a) The use of newly collected and analyzed scheduling process data will allow for a much more realistic modeling of many of the decision facets inherent in a scheduling model This will especially be useful in the activity generation and conflict resolution stages of the model And, new sources of schedule planning data (described in Part II of this thesis) will be used to move from static to dynamic activity planning, which involves removing the sequential planning steps found in previous models and replacing them with variable activity attribute planning steps, which depend on each individual and their current context

Current models do not take into account many important decision facets of the activity generation stage (Roorda et al 2005b) For example, the collection of process data in the CHASE dataset shows that differing types of activities have variable planning horizons This means that certain types of activities can be planned routinely, in advance, or spontaneously, and this distinction can have important effects as to how these activities are scheduled Models of planning horizons for different activities have been developed (Mohammadian and Doherty 2006), but have yet to be implemented within an activity-based modeling framework Additionally, the activity generation stage should consider the dynamics and history dependence underlying the need for new activities, as certain models have begun to do (Timmermans and Ettema, 2006) This thesis, then, will specifically focus on accounting for the timing between activities and the factors which account for this timing using new sources of long-term activity planning data

The conflict resolution and activity scheduling methods in TASHA, SCHEDULER and others are based on assumed activity priority alone Research on conflict resolution by Roorda et al (2005b) has shown that this is often not the case in a substantial number of conflicts Activity conflict resolution is actually a complex decision making process which is usually simplified in modeling systems through the use of priority rules alone However this simplification leads to situations such as those found in TASHA, where an activity can never be removed from the schedule once added (Roorda et al 2005a) or in ALBATROSS where an activity is never even modified once added (Arentze et al 2000) Clearly these situations are both oversimplifications of actual behavior and may lead to overestimation of the occurrence of high priority activities Some work has been done on evaluating characteristics of activity conflicts and identifying resolution strategies (Roorda et al 2005b) Additionally, Ruiz and Timmermans (2006) estimated a hazard model for activity conflict resolution, but the model was only applicable to activities inserted between preplanned activities and only considers timing and duration changes to the activities. It is clear that a more general model of activity conflict resolution is needed.

A more basic area in which further research is needed is in extending the scheduling model to a full week period, rather than developing a daily activity pattern alone. All of the models mentioned focus only on daily patterns, and therefore could potentially miss out important day-to-day scheduling process characteristics. Therefore the model will be developed to take into account a weekly schedule creation, as it is more likely how people actually think about making their schedules, as shown by the large number of activities that are neither routine nor spontaneous, but were pre-planned within the weekly period in the CHASE results (Mohammadian and Doherty 2006).

Another area of rule-based microsimulation modeling that has often been discussed and conceptualized but rarely implemented is the integration of the network assignment results into the activity scheduling stage. Often activity-based models create detailed activity schedules using microsimulation, but then aggregate the resulting flows into the O-D matrices used in traditional travel demand models for critical time of day periods. These O-D matrices are then assigned to the network in the same manner as in traditional models. This leaves out much of the detailed flow data from the activity model and makes the activity models not truly representative of traveler behavior. The model should therefore incorporate individuals' perceived travel time in the scheduling stage and allow the individual to learn from past results to make appropriate route selection. Therefore a network assignment approach which integrates directly with the activity planner at a disaggregate level is needed.

The final aspect missing in currently operational models is an analysis of the transferability of the model and a validation of the model results. Since the transferability issue is one of the major criticisms of the traditional model, it would be valuable to show that activity scheduling behaviors are in fact transferable across populations. Additionally, validation is important to show that the models are actually working, and show improvement over traditional models. Also, an analysis of the sensitivity of the various models to key policy variables related to planning behavior is needed. The purpose of this research, then, is to address all of these outstanding issues found in current models in a fully operational regional microsimulation framework.

4. THESIS ORGANIZATION

The thesis is organized in two major parts, in addition to the preceding introductory material. The introduction to this work detailed the review of previous work in activity-based modeling and identified significant research gaps still needing to be addressed. The following parts of the thesis, then, detail how the ADAPTS model was developed in order to address these gaps in the research. The first part of the thesis documents the development of the ADAPTS model itself, while the second part of the thesis discusses the data collection efforts undertaken to support the model development. Note that although many of the components of the ADAPTS model depend on the data collection effort, the development of ADAPTS is presented here first as it forms the major portion of the work. Brief descriptions of the data collected are provided along with each component model with appropriate references to the later portion of the thesis, where more detail is provided.

Part I of the thesis documents all of the steps undertaken in the development of the ADAPTS model. In this part an introduction and overview of the ADAPTS framework is presented along with the details about the simulation computer code development and its implementation for the Chicago region. Each component in the overall framework is also discussed in separate chapters. The chapters for each model component generally have separate literature reviews of previous work, model formulation and estimation details and calibration and validation results, where applicable. There is also a separate discussion of the overall model validation, when all the components are implemented in the ADAPTS simulation framework.

In Part II of the thesis, the design and implementation of a new GPS-based personal travel survey, called the Urban Travel Route and Activity Choice Survey (UTRACS) is discussed. A detailed review of previous work in household and personal travel surveying using GPS data is presented in this section. The new survey was designed based on the review of existing work and data needs identified for ADAPTS. This survey design and the data processing algorithms which support it are also discussed in Part II. Finally, the implementation details and results of the survey conducted from 2009 to 2010 in the Chicago region are discussed.

PART I: ADAPTS MODEL DEVELOPMENT

5. INTRODUCTION

Activity-based analysis has provided new and innovative ways to model travel demand and allowed for significant improvements in the understanding and forecasting of travel behavior. The realism and explanatory power of activity based modeling, especially when developed into a full microsimulation modeling system, continue to improve. However, it has been recognized that significant issues still exist in all activity-based microsimulation systems and that there are areas where theoretical and practical developments still need to be made (Litwin and Miller 2004), including in modeling the underlying decision processes behind activity scheduling, improving the representation of time and representing the interdependence between the various decisions underlying the activity scheduling process (Miller 2005).

However, probably the most significant issue which has often been observed is that most models that are developed so far are designed to estimate executed patterns of activities, with no consideration for modeling the underlying process of how those activity patterns were actually formed (Garling et al. 1996, Litwin and Miller 2004, Lee and McNally 2006). Thus, activity-based models are designed to fit existing revealed activity patterns, and most work well for this purpose. Since the models do not represent the actual underlying scheduling processes, they are not sensitive to potential changes in these processes. However, changing the activity scheduling behavior of individuals is a growing area for travel demand management policy, and in fact many other transportation policies may induce changes to the actual planning and scheduling processes themselves. Therefore, it is important that activity based travel demand models can represent these types of policies. For these reasons, a new framework for activity scheduling, the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model, has been developed.

This part of the thesis presents a framework for developing a fully dynamic activity planning and scheduling model for use in an activity-based microsimulation modeling system. A fully dynamic scheduling model treats activity planning steps as discrete events within the simulation, meaning that activity planning, modification, and execution are simulated along the same timeline. This system allows activities to be planned in a manner more closely approximating actual scheduling behavior, with activity scheduling decisions intertwined with actual activity execution. It is therefore able to respond to changes and new opportunities which may occur during the simulation. The underlying fundamental concept of this framework is the extension of the activity planning horizon, which had previously been applied to the activity itself (Doherty and Mohammadian 2003), to the planning of the individual activity attributes. Therefore, in addition to an activity planning horizon model (Mohammadian and Doherty 2006), there will also be a timing planning horizon, a location choice planning horizon, mode choice planning horizon, etc. Each of the planning horizons will define a specific time within the overall simulation timeline when the attribute selection decision is made, allowing for much more complex interdependencies between attribute decisions. For example, in a model of this type, the location decision could depend on a previous mode decision, or vice versa, and both decisions could depend on many other scheduling decisions made in the intervening time between the general activity plan (activity planning horizon) and the individual attribute activity horizons.

The rest of Part I is organized as follows. First, the general framework of the ADAPTS activity scheduling model is described and potential data sources are discussed. This is followed by the introduction of a new population synthesis routine developed to create the agents used in the ADAPTS model simulation. Next, each stage of the activity planning and scheduling process employed in the model is discussed. This includes the activity generation, plan order determination, attribute planning and activity scheduling models which form the ADAPTS activity planning model. Also discussed is the new trip assignment and traffic simulation routines developed to integrate dynamically with the activity planner. The simulation environment development and results of an initial implementation for the Chicago region are also documented. Finally, conclusions drawn from the ADAPTS model development and implementation process are discussed along with possibilities for future research on dynamic rule-based activity planning and scheduling models.

6. ADAPTS DYNAMIC SCHEDULING MODEL FRAMEWORK

The fundamental concept underlying the framework of the dynamic activity scheduling and planning model is to treat activity planning events as individual discrete events within the overall simulation framework. Consequently, an activity schedule is created and modified over time, and the attributes of each activity are not necessarily planned in any given order, which contrasts with the assumptions usually made about the sequential planning process, as in ALBATROSS (Arentze et al. 2000), TASHA (Miller and Roorda 2004), and others. Furthermore, there are separate events for the planning of each attribute of each activity, so that party composition, location choice, time-of-day decisions and mode choice decisions are all represented by separate planning events. The execution of these planning events occurs along with the execution of activities and travel.

The scheduling model itself is a sub-model in a larger overall activity-based modeling framework, a proposed outline of which is shown in Figure 1, where long-term decisions, such as housing choices, job choices, vehicle ownership, household composition, etc, are estimated in a long-term simulation. This information feeds in to the short term simulation of the activity-travel pattern, the results of which are then fed back to the long term simulation. The combination of the long term land use simulation with the short term activity-travel simulation defines an integrated land-use transportation microsimulation model. However, the focus of this thesis is on the development of the new activity-travel model formulation alone.

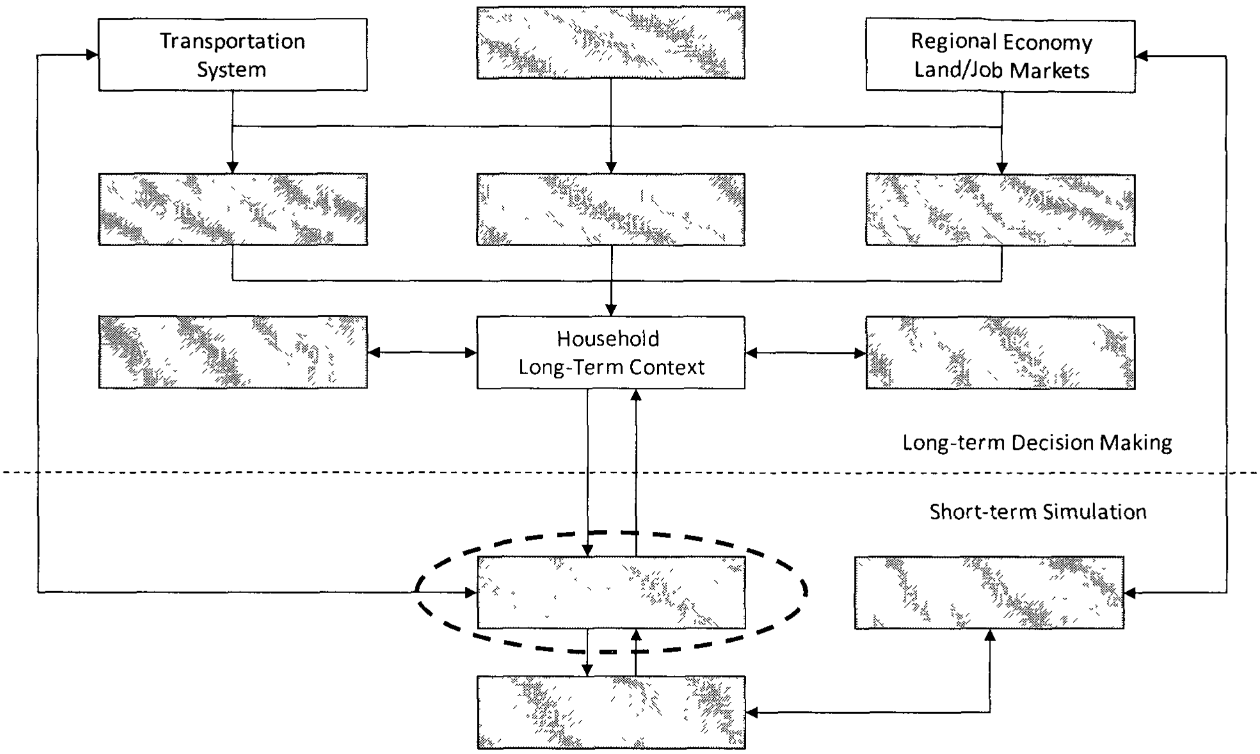


Figure 1. Integrated Land-Use Transportation Framework

The ADAPTS model simulates activity planning and scheduling over a specified timeframe, and integrates directly with a traffic simulator by outputting a list of trips to assign at each time step, which in turn feeds back simulated trip results and updated network characteristics to be used in planning for the next timestep and updating scheduled activities as necessary. As such, the ADAPTS model is dynamic, with planning and scheduling occurring in a time-dependent manner and impacted by the results of the time-dependent traffic network. An overview of the ADAPTS simulation framework is shown in Figure 2. The simulation process includes three primary stages: initialization of the simulation environment, household and individual planning at each time step, and trip vector generation and traffic assignment at each time step.

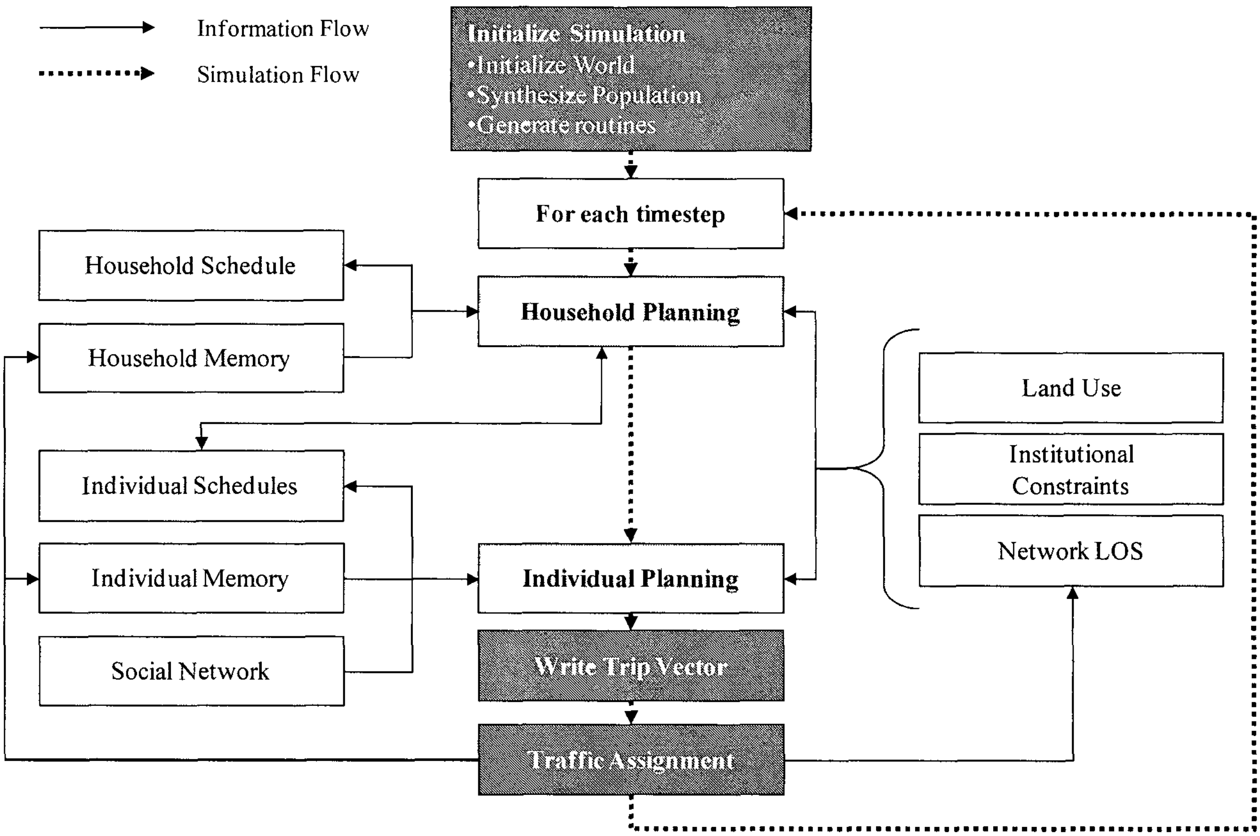


Figure 2. ADAPTS Simulation Process Framework

The ADAPTS model planning and scheduling model is called at each timestep for both household and individual agents to update/plan their activity schedules; shown in Figure 2 as "Household Planning" and "Individual Planning". The planning and scheduling model simulates the dynamic process of schedule formation and accounts for the varying interdependencies and potential differences in planning times among the various attributes of the activity. This forms the core of the ADAPTS model. For example, an activity can be added and a location chosen at the same time, but the timing for the activity may be left open. If the timing is decided later, it will therefore depend on the location choice. However, the timing may not depend on the location choice at all, i.e. it could be planned first or even at the same time. It is likely that there are fundamental differences between, for example, location choice decision processes when timing is known, versus when timing is unknown. This framework attempts to capture those effects.

At the conceptual level, the planning and scheduling model can be thought of as splitting the activity scheduling process into three distinct phases. The first phase is activity generation. In this framework, activity generation refers only to the highest level decision of whether or not to add an activity of a certain type, i.e. all other activity attributes are left unspecified. However, certain aspects of the activity which are assumed to be fundamental to the activity episode are specified at generation. Such aspects include the flexibility values for the attributes, the plan horizon of the activity, and plan horizons for each attribute, which determine when and in what order the attribute decisions are later made. This portion of the generation process, referred to as the "Planning Order Model", forms the core of the ADAPTS planning system and allows for the dynamic simulation of activity planning. The second phase of the model framework is activity planning. In this phase, the actual values of the various activity attributes are specified, in the order and at the time determined by the planning order model. This means that in the ADAPTS framework, the attributes can be determined in any order, with attributes planned later being dependent on the already planned attributes, leading to a system of conditional dependencies between the various attribute choice models. Finally, the last phase of the framework would be the actual activity scheduling, where the activities would be added to the planned schedule and conflicts would be resolved.

The framework for the ADAPTS activity scheduling model is shown in Figure 3. The figure shows the process that an individual agent within ADAPTS follows at each timestep in building up and executing the activity-travel pattern. It presents activity scheduling as a dynamic process, completed over time with the final executed schedule resulting from a series of decisions. The high level decisions represented in the framework include: whether to add a new activity, whether to update attribute values for an existing activity, whether to resolve conflicts between planned activities, and finally, whether a planned activity can be executed. As shown below, each high-level decision contains a number of models which represent how aspects of the decision are made. For example, if the individual decides to add a new activity, this will encompass several subsequent decisions, which are captured in the planning order model and planning horizon models. One important note regarding this process, however, is that it applies only to the non-routine activity scheduling. Within the ADAPTS framework, a routine "skeletal schedule" is first developed through a separate, though very similar, simulation process around which the non-routine planning then takes place, as shown in Figure 3. The only difference with the routine simulation is that the planning order model is eliminated and attributes are modeled simultaneously.

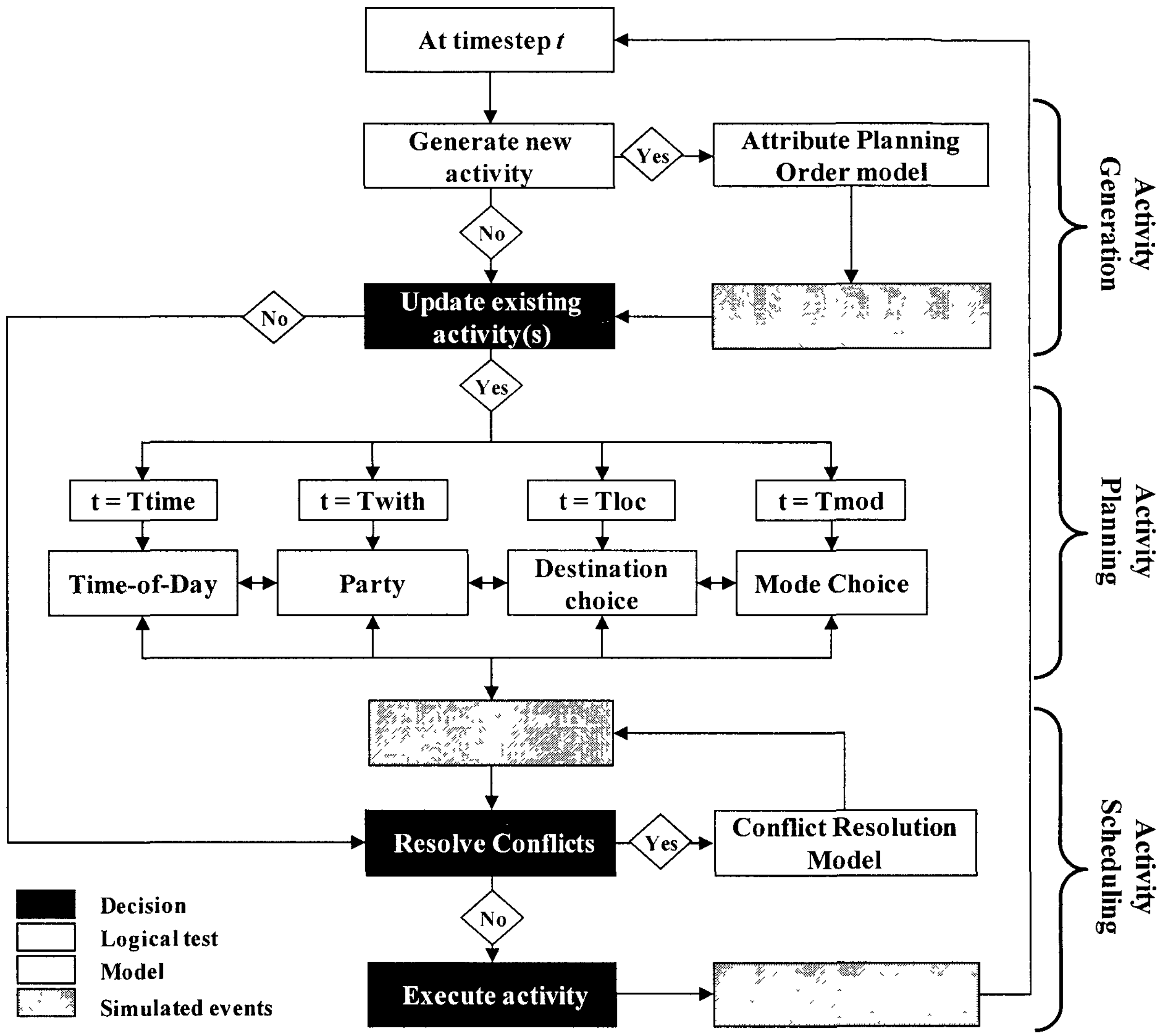


Figure 3. ADAPTS Scheduling Process Model Framework

As is shown in Figure 3, the framework consists of a series of four top-level decisions (*Generate New Activity, Update Existing Activity, Resolve Conflict* and *Execute Activity*) which are evaluated in order for each time step to determine if further action is required.

The *Generate New Activity* decision is itself a model, i.e. the activity generation model, while all of the other decisions are rules followed based on the individual agent schedules at each timestep. Under each top level decision are further sub-models, which refine or change the planned activity schedule or execute an activity as needed The *Generate New Activity* decision includes the activity generation model discussed in Chapter 8, which returns the probability for generating an activity at the current timestep on which the decision is made It also includes the *activity planning order* sub-model found in Chapter 9, which is called if an activity is generated and sets the plan horizons for the activity

The *Update Existing Activity* decision involves searching the agents' schedules for plan flags set by the plan order model If a flag is set for the current timestep, the appropriate attribute planning model is then invoked The attribute plan models which are involved in the *Update Existing Activity* decision are the *destination choice, mode choice, start-time duration* and *party composition* models, which are allowed to be called in any order The attribute models are all intended to be *planning constrained* models, in that the decisions will depend on the attributes which have been previously planned Currently however, only the *destination choice* and to a very limited extent the *mode choice* models have been implemented with planning constraints, as will be discussed in Chapter 10

Finally, the *Resolve Conflict* and *Execute Activity* decisions are based entirely on the current state of the schedule The *Resolve Conflict* decision is made whenever a new activity is to be added to the schedule of an agent, after it has been sufficiently planned (i e after the start and duration are known) This decision analyzes the state of the schedule and the attributes of the activity to determine if a conflict will occur If so, a conflict resolution model and set of scheduling rules are used to determine how the activity conflict will be handled The conflict resolution and scheduling rules are presented in Chapter 11 Once any conflicts are resolved, the *Execute Activity* decision rule searches the schedule for any activities set to begin in the current time period If any activities are to start, a new trip object is generated and sent to the *Trip Assignment and Traffic Simulation* model discussed in Chapter 12

The next several Chapters discuss the development of the individual components of the overall modeling framework, starting with population synthesis, which is used to initialize the simulation

7. POPULATION SYNTHESIS

7.1. Introduction

The first model component within the ADAPTS model system is the population synthesizer as shown in Figure 2 Population synthesis is recognized as an integral component within activity-based modeling Starting with the development of the TRANSIMS population synthesizer (Beckman et al 1996), increased focus has been directed at developing synthetic populations for use in travel demand microsimulation (Roorda et al 2007, Bhat et al 2004, Yagi and Mohammadian, 2008, Frick and Axhausen 2004) and many other agent-based microsimulation applications (Wheaton et al 2009, Ryan et al 2009) Population synthesis generally utilizes a sample of households at an aggregate geography combined with marginal data on household characteristics at a disaggregate geography to generate a set of households which satisfy known marginals at the small-area level Population synthesizers often use a well known statistical technique, Iterative Proportional Fitting or IPF (Deming and Stephan, 1940), and probabilistic selection in order to generate synthetic populations, although other procedures have recently been developed (Voas and Williamson, 2000) Either way, a population synthesizer creates copies of sample households and locates them geographically in order to replicate the full population of the study area For a more in depth discussion of the IPF procedure and basic population synthesis techniques see Beckmann et al (1996), Arentze and Hofman (2007) or Hobeika (2005) among others

The increasing focus on population synthesis has resulted in recognition of some limitations of the basic synthesis method This work aims to improve the methodology behind the basic population synthesis routine in order to account for multiple-levels of analysis units/control variables, which was a limitation to earlier population synthesizers This chapter includes a discussion of the literature on population synthesis, a description of the newly developed synthesis method, validation of the new method, evaluation of its computational performance and finally, a discussion of the value of the new method and directions for future work

7.2. Previous Work in Population Synthesis

The methodology behind most population synthesizers used in travel demand modeling is generally derived from the synthesizer developed by Beckman et al. (1996) for the TRANSIMS project, although some recent work has also addressed the Combinatorial Optimization approach (Ryan et al. 2009; Voas and Williamson, 2000), or combinations/permutations of both (Ye et al. 2009; Pritchard and Miller, 2011). During the development of different population synthesizers, many limitations of the basic methodology have been observed. Subsequent research has focused on attempts to correct for these deficiencies and extend the usefulness of synthesis methods (Ye et al. 2009; Guo and Bhat 2007). Several problematic issues relating to population synthesis that have been observed at various times include: zero-cell issues arising from using sample data, biases introduced due to rounding the joint-distributions, biases introduced due to simulation and lack of multiple levels of control (Beckman et al. 1996, Voas and Williamson, 2000, Pritchard and Miller, 2009; Guo and Bhat 2007). Different strategies have been proposed to address these issues, for example the zero-cell problem has been addressed by "tweaking" the joint-distribution from the IPF procedure (Beckman et al. 1996; Guo and Bhat 2007) and by limiting the number of control variable categories (Auld et al. 2009; Guo and Bhat 2007).

The limitation of population synthesis methods to only one analysis-level has recently begun to receive more attention. Traditionally, population synthesizers only consider control variables for one level, since joint-distributions between household and person control variables cannot be constructed. Therefore the IPF procedure and selection procedure as found in Beckman et al (1996) cannot be implemented directly for both household and person level variables simultaneously (Guo and Bhat 2007). Researchers have attempted to overcome this in several ways, including household reconstruction methods (Pritchard and Miller, 2009) or using population characteristics to impute household-level distributions (Arentze and Hofman, 2007). Recent work has focused on methods to address the issue directly in the synthesis procedure, rather than as a reconstruction step. Guo and Bhat (2007) account for person-level controls by developing joint-distributions for both individuals and households separately, then synthesizing households while considering whether the person or household level constraints would be violated beyond a given threshold, although only the household distribution is considered when drawing households. Ye et al. (2009) developed the only previous attempt to directly and simultaneously control on multiple levels of which the author is aware. They used an iterative reweighting procedure to heuristically solve for household weights considering both household and person constraints together prior to the household selection procedure. The methodology presented here is a new, efficient procedure for considering joint multi-level controls implemented directly in the selection stage, which builds on the basic IPF and household draw procedures.

7.3. Development of Population Synthesis Procedure

The population synthesis procedure developed for ADAPTS is accomplished in two primary stages, similar to most other population synthesizers. The two primary stages are the creation of the multidimensional distribution table for each analysis area and the selection of households to be created for each analysis area. A brief description of the implementation of these procedures, noting where they differ from other population synthesizers, is given below, as is a description of the procedure behind some of the new features such as the multi-level control scheme. Figure 4 shows a flow control diagram that describes the basic operation of the synthesis program. Note that from this point forward, the sub-regional level of the geographic area, of which the Public Use Microdata Area (PUMA) is an example, will be referred to simply as "region", while the analysis zones within the region will be referred to as 'zones'. This terminology is adopted as any geographic types can be used in the method as long as sufficient data exists.

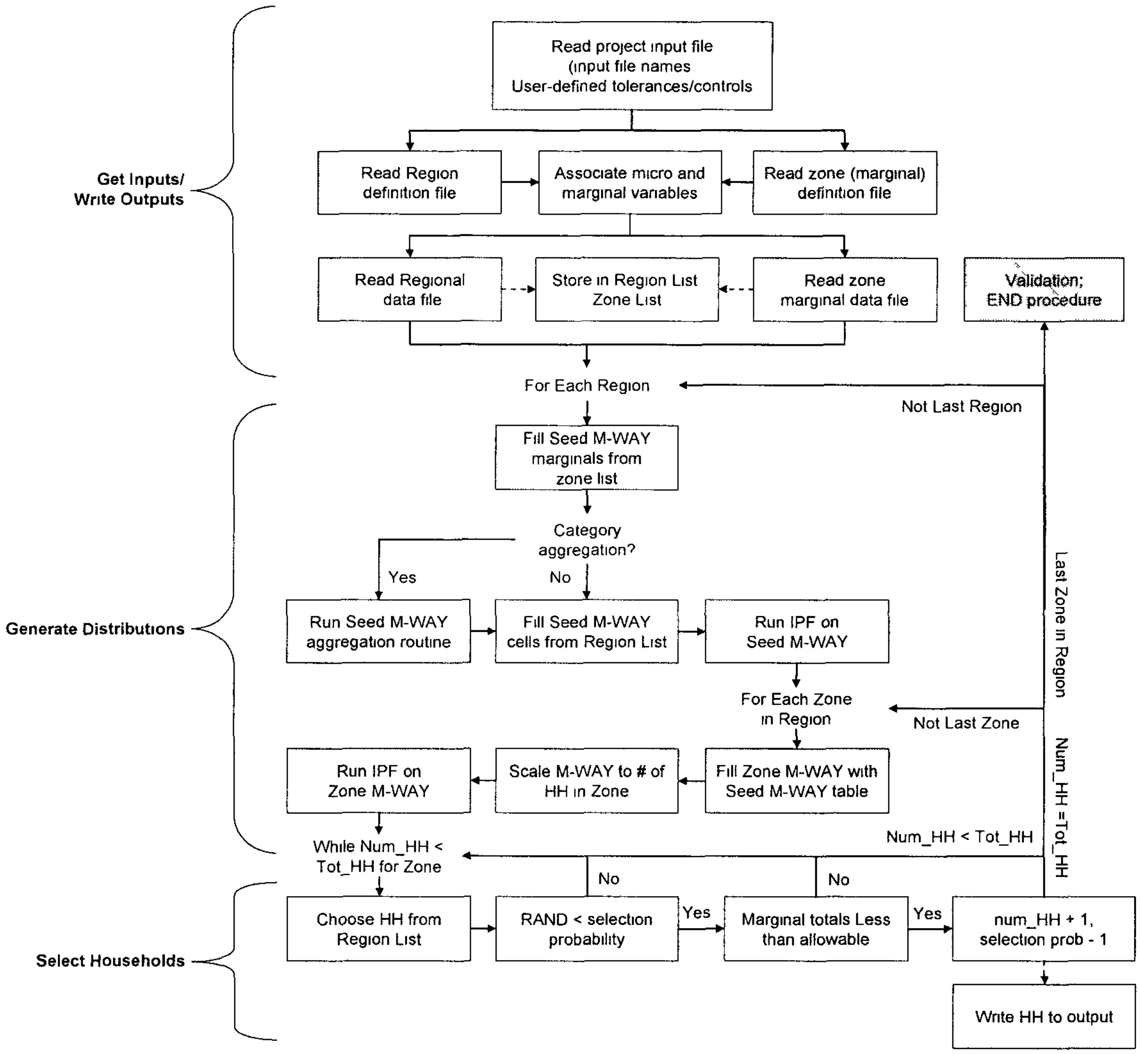


Figure 4. Population Synthesis Procedure Overview

7.3.1 Generation of Multidimensional Distribution Table Using IPF

The multidimensional distribution table for each region is created in a similar manner as the distribution tables in other population synthesizers (Beckman et al. 1996, Guo and Bhat 2007). First the marginal distributions from the marginal data file are added to the multi-dimensional distribution table for the region. After this, the optional category aggregation routine is run to reduce the size of the distribution table. The micro-level sample data is then added to the table. This is accomplished by summing the household weights for all households that correspond to each cell in the table. The complete distribution is then fit to the marginal totals through the use of the

IPF procedure described above. This creates the final region-level multi-way table that is used to seed all of the zone-level distribution tables.

After the region-level table is created, the program cycles through the list of all of the zones contained within that region. For each zone the seed matrix cell values are adjusted so that the total matches the desired number of households to generate. The zone-level multi-way distribution is then adjusted to match the zone marginals by again running the IPF procedure. Originally, the region-level seed matrix was used as an additional constraint in the IPF procedure over all of the zones simultaneously, however this approach was discontinued after it was observed that doing so increased the difficulty of obtaining convergence of the IPF procedure with relatively little benefit to the accuracy of the resulting distributions as was observed by Beckman et al. (1996). After this stage was completed for each zone, the desired multi-way table for each zone was known and the household selection procedure was started. The same procedure used to develop the household characteristics distribution table was then used to generate a person-level distribution table. Both tables were then used in a new multiple control-level household selection scheme discussed below, to generate the final synthesized populations.

7.3.2 Multi-level Control Methodology

This section discusses the methodology used for multi-level control, implemented within the basic population synthesis program described above. Multi-level control allows population characteristics to be replicated when creating the synthetic population for more than one analysis level, with one level such as households serving as the base level of analysis and another sub-level which is contained within the base-level. It should be recognized, however, that there is no requirement that the analysis be used only for synthesizing households/individuals. Any situation where marginal and sample data is available for both a base- and sub-level of analysis (i.e. firms/employees, households/vehicles, buildings/tenants, etc.) can be synthesized using the program. The only limitations are that the membership size of the sub-level within the base level must be used as a control (i.e. household size if using household/individual) and the sample data for the base- and sub-levels must be linked by unique identifiers. The second requirement is necessary due to the fact that the program utilizes a procedure where the base-units are generated and its component sub-units are copied with it rather than synthesizing each sub-unit separately. Since the sub-units are copied along with the base unit there must be a link between the base- and sub-unit sample data. For clarity the base- and sub-levels of analysis are referred to hereafter as simply household-level and person-level.

7.3.3 Household Selection Probability Considering Person-level Constraints

One feature most population synthesizers share is the creation of synthetic households through probabilistic selection. This procedure involves setting a probability for selecting a sample household into the synthetic population based on the sample weight of the household, the number of total households required, the number of households of the current type already generated, etc. This is the basic procedure followed in the synthesizer by Beckman et al (1996). Selection probabilities are assigned for households which are then replicated through simulation. The probabilities increase with the weight of the household and decrease as the required frequency of the current household type is reduced through the simulation process. The required frequency of each household type is taken from the estimated household joint distribution created through the IPF process. Population synthesizers may depart from this basic methodology, as in the procedure developed by Ye et al. (2009), where the frequencies determined in the IPF procedure are used in a heuristic iterative solution to set household weights such that person-level constraints are satisfied. Even in this case, however, simulation is still used to create the synthetic households using the reweighted IPF results. The general selection probability as described in Beckman et al (1996) is shown in Equation 1.

$$P_{i,c} = \frac{W_i}{\sum_{k=1}^{N_C} W_k} \tag{1}$$

where,

$P_{i,c}$ = probability of selecting household i, of household type c

W_i = household weight for household i

This equation states that the probability of selecting the current household i of a given demographic type C is equal to the weight of the current household divided by the sum of the weights of all other households in the sample of the same type. This selection procedure ensures that households with a higher sample weight are selected more frequently when synthesizing the households. This selection probability does not account for differences between households on the person-level. Therefore, a new selection probability, shown in Equation 2, was developed that explicitly accounts for the person-level distribution when synthesizing the households.

$$P_{i,c} = \frac{W_i \prod_{j=1}^{N_{per,i}} \frac{MWAY^*_{per}(v_{1,j}, v_{2,j}, \ldots v_{n,j})}{N_{remain}}}{\sum_{k=1}^{N_C} (W_k \prod_{l=1}^{N_{per,k}} \frac{MWAY^*_{per}(v_{1,k}, v_{2,k}, \ldots v_{n,k})}{N_{remain}}} \tag{2}$$

where,

$P_{i,c}$ = probability of selecting household i, of household type c

W_i = household weight for household i

$N_{per,i}$ = number of people in household i

$MWAY^*_{per}(v_{1,j},\ldots v_{n,j})$ = remaining cell frequency in zonal person-level joint distribution

$v_{i,j}$ = index of control variable i, for person j

N_{remain} = number of individuals not yet created in zone

N_c = remaining households in sub-region sample of type c

The selection probability defined in Equation 2 has the same form as Equation 1, with the addition of the product terms in the numerator and denominator. These product terms are essentially the probability of observing a household composed of each individual household member given the remaining persons to be synthesized according to the person-level joint distribution, $MWAY^*_{per}$. This selection probability is derived from a straightforward application of Bayes Theorem, i.e. the probability of selecting the current household H, is the probability of observing household H given the current household type C. This is equivalent to the probability of observing each member in the household together divided by the sum of the probability of observing each household member together for all households of the same type, assuming no correlation between the probabilities for individual household members. This assumption is generally incorrect in actuality and would cause problems if we were reconstructing households based on individual probabilities However, since we are only using the individual probabilities to weight household selection this does not matter Even if unlikely households are weighted the same as likely households on the basis of their individual members, the likely household type is observed more frequently in the sample data and will therefore be more likely to be generated So the assumption of independent individual probabilities is corrected by the household weighting term to produce the proper results This can be reduced even further with the proper choice of household-level control variables This new selection probability allows the household selection procedure to generate households with individuals that most closely match the required person-level joint distribution This is best demonstrated with an example, shown in TABLE I

In this example, 25 households of the same type are synthesized from a sample of four households with the person-level joint distribution shown in Part a) The basic procedure is shown in Part b), where all four households have the same selection probability since they have the same weight and the person-distribution is ignored In this case, the same number of each household is generated with the resultant synthesized person-level distribution clearly not matching the expected Part c) then, shows the results when the new selection probability is used Now the households with more frequent person types in the person-level distribution (HH1, HH4) are generated more than the others Note that in this simple situation the person-distribution is matched exactly The example shows that with the new selection probability the person-level marginals and joint distribution are matched when the household and person data are consistent

TABLE I
SELECTION PROBABILITY CALCULATION EXAMPLE

a) Starting Data

Microdata sample:

HH1: 1 employed male, 1 employed female, HHweight = 1
HH2: 1 unemployed male, 1 employed female, HHweight = 1
HH3: 1 unemployed male, 1 unemployed female, HHweight = 1
HH4: 1 employed male, 1 unemployed female, HHweight = 1

Person-Level Joint Distribution:

	Employed	Unemployed	Total
Male	20	5	25
Female	10	15	25
Total	30	20	50

HH-Level Joint Distribution:

		Total
HHSize = 2	25	25

b) No person control

Selection Probabilities (Equation 1):

$$P(HH1) = P(HH2) = P(HH3) = P(HH4) = \frac{(1)}{(1+1+1+1)} = 0.25$$

Synthesized Person-Level Distribution:

	Employed	Unemployed	Total
Male	12.5	12.5	25
Female	12.5	12.5	25
Total	25	25	50

HH1_total = 0.25 x 25 = 6.25
HH2_total = 0.25 x 25 = 6.25
HH3_total = 0.25 x 25 = 6.25
HH4_total = 0.25 x 25 = 6.25

c) With person control

Selection Probabilities (Equation 2):

$$P(HH1) = \frac{(20/50)(10/50)}{(20/50)(10/50) + (5/50)(10/50) + (5/50)(15/50) + (20/50)(15/50)} = 0.32$$

$$P(HH2) = \frac{(5/50)(10/50)}{(20/50)(10/50) + (5/50)(10/50) + (5/50)(15/50) + (20/50)(15/50)} = 0.08$$

$$P(HH3) = \frac{(5/50)(15/50)}{(20/50)(10/50) + (5/50)(10/50) + (5/50)(15/50) + (20/50)(15/50)} = 0.12$$

$$P(HH4) = \frac{(20/50)(15/50)}{(20/50)(10/50) + (5/50)(10/50) + (5/50)(15/50) + (20/50)(15/50)} = 0.48$$

Synthesized Person-Level Distribution:

	Employed	Unemployed	Total
Male	20	5	25
Female	10	15	25
Total	30	20	50

HH1_total = 0.32 x 25 = 8
HH2_total = 0.08 x 25 = 2
HH3_total = 0.12 x 25 = 3
HH4_total = 0.48 x 25 = 12

7.3.4 Household Selection Procedure

The new household selection probability requires more calculation than the basic household selection probability, due to the sum in the denominator which contains the products of the probabilities for each individual. Under the base methodology, the sum of the weights in the household sample can be calculated once before the synthesis procedure begins and the number can be reused, but the new methodology requires the sum to be recalculated every time the probability is calculated, as the product changes whenever a household/person is synthesized. Therefore a new selection procedure was needed to ensure that populations could be synthesized more efficiently. The new procedure is described in this section.

The procedure behind the new synthesis methodology is as follows for each sub-region (i.e. geographical area at which sample data is available):

1. Generate Sub-region level HH and Person Joint Distributions
    a. Create sub-region household-level joint distribution from household sample data
    b. Create sub-region person-level joint distribution from person sample data
    c. Use IPF to fit household joint distribution to HH marginals from marginal data
    d. Use IPF to fit person joint distribution to person marginals from marginal data
2. Get next geographic zone within the sub-region
3. Generate zone level HH and Person Joint Distributions
    a. Seed zone HH joint distribution with sub-region joint distribution
    b. Seed zone person joint distribution with sub-region joint distribution
    c. Use IPF to fit HH joint distribution to zone marginal data
    d. Use IPF to fit HH joint distribution to zone marginal data
4. Run household selection procedure
    a. Get next household, H, randomly from the sub-region sample
    b. Calculate household selection probability *P* using Equation 1.
    c. Make *N* attempts to add copy of H with probability *P*, with *N* as remaining houses of current type needed in HH joint distribution

d. Reduce cell in zone HH joint distribution by number of H added

e. Remove H from sub-region sample

f. If households remain in sub-region sample, return to a.)

5. Add all removed households back to sub-region sample
6. If iterations are less than max and households still needed, return to 4.)
7. If zones remaining in sub-region, go to 2.)
8. If Sub-regions remaining, get next sub-region and go to 1.) else finish.

The procedure allows for simultaneous household and person control (as described in the previous section) while enhancing the efficiency of the algorithm. In the traditional household selection procedure (Beckman et al. 1996; Guo and Bhat 2007), the list of households in the sub-region sample is searched through many times in order to generate the required number of households. The search procedure generally occurs as follows:

1. Get current household from household list
2. Set selection probability based on Equation 1 multiplied by remaining frequency of household type divided by total remaining households
3. Determine if household is added based on selection probability
4. Return to step 1, if households are still needed in zone

This procedure generally requires much iteration through the sub-region household sample, a process which takes a fairly long time to complete when the new selection probability calculation described in Section 3.1 is used. The new selection procedure simply searches once through the sample household list for each zone. For each household in the sample, the procedure calculates the selection probability then makes a number of attempts to copy the household equal to the remaining frequency in the household joint-distribution for the household type. Each time a copy of the household is successfully added, the probability is updated. After all attempts have been made, the household is removed from consideration, so that it does not figure into the selection probability calculation for later households. This continues until the all households in the list have been searched, at which point, the full population is synthesized. Note that the list is searched in random order to ensure that any biases in the ordering of the sample data are not transferred to the synthetic population.

This process guarantees that the full population is synthesized in one pass through the sample list, greatly reducing the computational run time. However, due to random rounding during the synthesis procedure (i.e. if 3.4 household are required, this will be realized as either 3 or 4 households), marginal totals are sometimes violated. Therefore a marginal constraint is added to the selection procedure at both the household and person level. This constraint takes the form of an additional rule: if a household is to be added, neither the household or any individual within the household can cause any of the household or person-level marginals to be exceeded by more than a user-defined tolerance. If the marginal constraints will be violated the household is not added. This generally leads to the result that less than the full number of households are generated, usually due to inconsistencies and incompatibilities in the data. Therefore the selection procedure is run for up to a user-defined maximum number of iterations, at which point the marginal constraints are relaxed and the full number of households is generated.

Another problem sometimes arises due to the nature of the selection probability. When calculating the probability for a household, if one of the household members is not needed (i.e. has a remaining frequency of zero in the joint-distribution) the selection probability for that household goes to zero. This is an intentional feature of the procedure and is almost always desirable, but can occasionally cause problems when there are incompatibilities between the household and person-level data. For example, zones such as Block Group 170312704002 in Cook County, which has seven households of household-size four but only 20 total people, will cause the selection procedure to fail. In this example, after the fifth household is generated, there are no people left in the person-level joint distribution, so the household selection probability goes to zero and no households are selected no matter how many iterations are run. Therefore, on the final iteration of the procedure, if there are still households remaining to be generated, the program disregards all person-level controls and generates the remaining households based only on the household weights using the selection procedure seen in Equation 1.

7.4. <u>Population Synthesis Validation Results</u>

To assess the validity of the new person-level control methodology, a synthetic population created with the new routine was validated against the same population created without person-level control The validation for the person-level control procedure was conducted on 846 block groups in the Chicago six-county region where household and person-level marginal control incompatibilities were minimal Note that many block groups had populations less than the population estimated from the household size control variable, an error which causes less than the full number of households to be generated (since all person-level probabilities are set to zero before all of the households are generated) The selected block groups have a total of 553,387 household containing 1,498,482 individuals, approximately 20% of the total six-county population These block groups were selected such that there were no group quarters population and the differences between estimated population totals based on the household size control variables and the population totals in the person-level marginals was less than 2%, in order to separate out error due to the procedure from error caused by data issues Note that block groups with group quarters are excluded from this analysis only because including a marginal variable relating to group quarter status does not add anything to the person-level validation When generating synthetic populations for actual modeling purposes it is a straightforward procedure to add a group quarters control marginal at the household level which enables block groups with substantial group quarters populations to be generated In this manner, the validations run below are comparing the differences in procedure rather than differences due to data issues

Two separate populations were synthesized, one using only household controls referred to as *POP-HH* and one with an additional set of person-level controls referred to as *POP-PER* The household controls used for both populations were

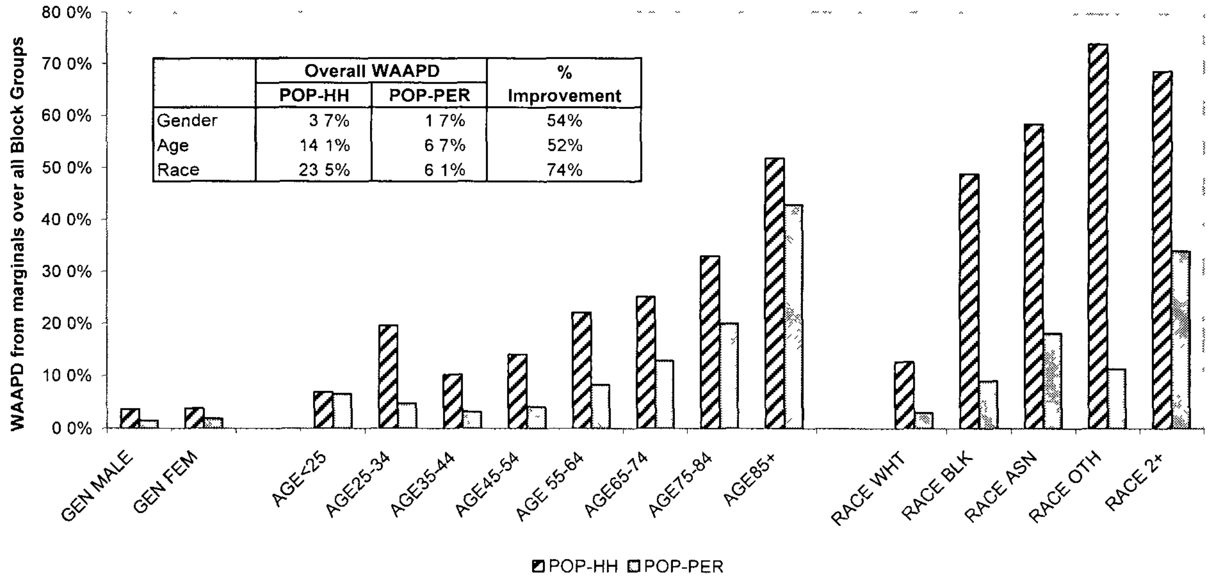
- Household size – 7 categories
- Household Income – 16 categories
- Household Number of workers – 5 categories
- Total Household Joint Distribution size – 560 cells

While the person-level controls used in generating *POP-PER* were

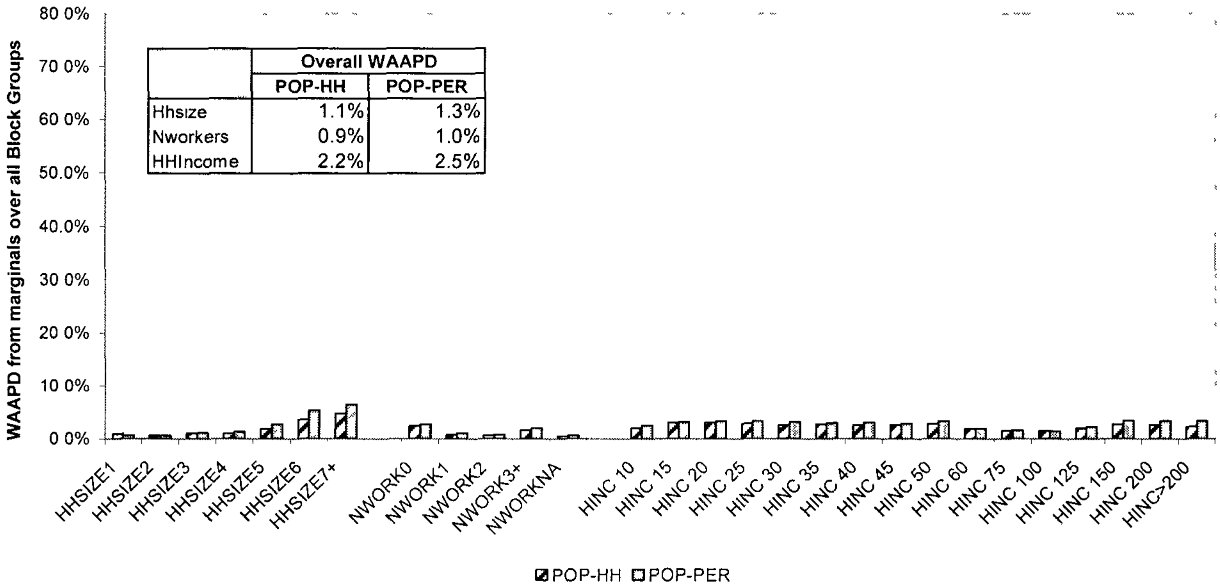
- Gender – 2 categories
- Age – 8 categories
- Race – 7 categories
- Total Person Joint Distribution size – 112 cells

Both synthetic populations were able to exactly match the total number of households required, with each generating the actual total of 553,387 households. In addition the total number of individuals generated was almost exact for each synthetic population, as expected even for the non-person control population due to the inclusion of a household size variable as a control. The POP-HH population contains 1,500,308 people, 0.1% more than required, while the POP-PER population contains 1,487,815 people, 0.7% less than required. The marginal fit comparison, in terms of weighted average absolute percent difference (WAAPD) between the known and synthesized marginal totals over all block groups, for both populations is shown in Figure 5. Note that the Native American/Alaskan and Hawaiian categories in the Race control are not shown as these categories represent less than 0.25% of the population in the region, although both exhibited similar improvement as the other categories.

The person-level comparison, shown in Figure 5(a), demonstrates a substantial improvement in fit between the POP-HH and POP-PER marginal totals on the person level, as expected. Overall there is an improvement in fit of between 52% and 74% over each person-level category, showing that the new routine allows a marked improvement in fitting to person level marginal control totals. As seen in the figure, even under person-level control, the average error associated with certain marginal categories can still be large, although always less than with no person control. This is due mainly to rounding errors and difficulty satisfying the marginal constraints for infrequent categories. The largest errors in the marginal fit are seen for the over-85-years-of-age category and the two-or-more-races category for the age and race marginals respectively, which each represent less than 2% of the total population. In fact all marginal categories which have a WAAPD of over 15% contain less than 5% of the population, meaning that the large errors are mostly the result of small category sizes.



(a)



(b)

Figure 5. WAAPD Comparison for (a) Person and (b) Household-Level Marginals

The household-level comparison in Figure 5(b) shows that the improvement in marginal fit using person-level controls comes at a minimal cost to the accuracy of the household-level marginals. All marginal control totals are matched fairly precisely in both the POP-HH and POP-PER synthetic populations, with larger errors again seen in the less frequent categories. All household marginal categories had under a 7.0% WAAPD value.

One point about the procedure should be noted regarding the relaxation of the person-level constraints used in order to ensure convergence when selecting households. It is clear that allowing the person-level constraints to be violated introduces errors into matching the expected person-level marginals, causing most of the differences seen in Figure 5(a). However, analysis shows that in general it is a very small number of generated households and individuals which contribute to these violations, so the impacts are most likely not particularly large. For the POP-PER synthetic population, on average over 97% of households (2% s.d.) and 95% of individuals (3% s.d.) were generated before the person-level constraints were relaxed.

The previous analysis only shows how the population matches the marginal characteristics. Therefore each synthetic population was also evaluated on how well the required household- and person-level joint distributions were matched. This is evaluated by estimating the Absolute Percent Difference between the synthesized and expected (from IPF) frequencies for each cell in each block group. This value is then averaged over all block groups to get an Average Absolute Percent Difference (AAPD) value for each cell in each joint-distribution. The AAPD values for each synthetic population are then plotted against the average cell frequency, along with a theoretical estimated AAPD from rounding error calculated as shown in Equation 3 below.

$$AAPD_i = \frac{\sum_{j=1}^{N_{BG}} APD_{i,j}}{N_{BG}}$$

$$APD_{i,j} = (1-p_{i,j})\frac{x_{i,j}-(x_{i,j}-p_{i,j})}{x_{i,j}} + p_{i,j}\frac{(x_{i,j}+1-p_{i,j})-x_{i,j}}{x_{i,j}} = \frac{2(p_{i,j})(1-p_{i,j})}{x_{i,j}} \tag{3}$$

where,

$APD_{i,j}$ = expected absolute % difference from value in cell i for block group j from rounding

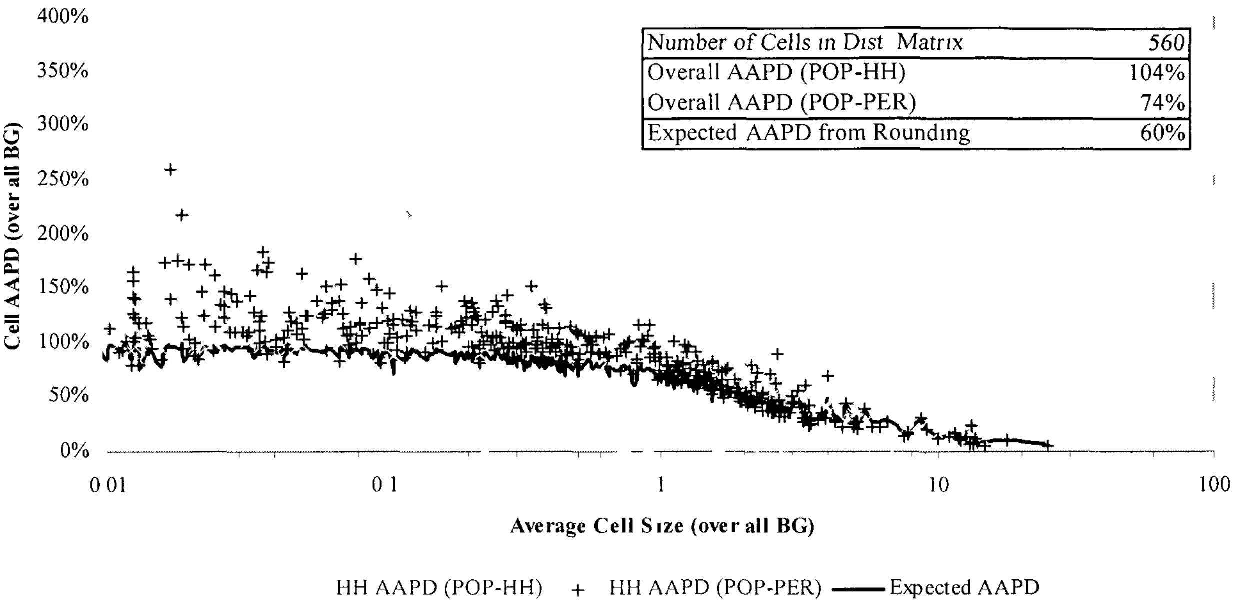
$AAPD_i$ = average APD for cell i over all block groups from rounding

$p_{i,j} = x_{i,j} \bmod 1.0$

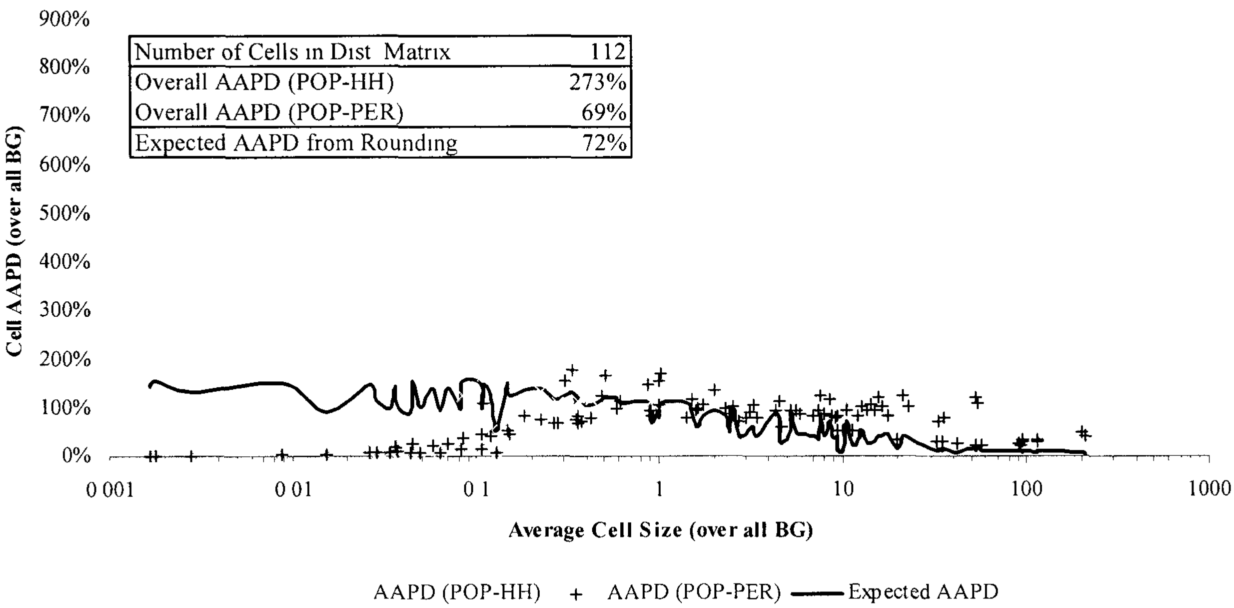
$x_{i,j}$ = value in cell i, of person - level joint distribution for blockgroup j

Equation 3 states that the expected absolute percent difference for each cell in the joint-distribution for each block group is the probability of rounding the cell down multiplied by the error caused by this plus the probability of rounding the cell up multiplied by the error caused from rounding up, where the probability is determined by the decimal portion of the actual cell value (i.e. a cell value of 1.2 will be rounding down 80% of the time and rounded up 20% of the time, so that 80% of the time the error is 0.2/1.2 or 16.7% and 20% of the time the error is 0.8/12 or 67%, for an average of 26.7%). The values for each block group are then averaged to get the AAPD value for each cell. These values are plotted, along with the AAPD values from the POP-HH and POP-PER populations in Figure 6 for both the household- and person-level joint distributions. Note that these values are plotted against *average* cell frequency, so that a cell with an integer average frequency will still have expected average rounding error.

Figure 6(a) shows the results of the comparisons of the AAPD values for each cell in the household distribution matrix, for both the POP-HH and POP-PER synthetic populations. The figure shows that the populations produced through both procedures replicate the household-level joint distribution reasonably well, with the AAPD values approaching the theoretically expected value due to random rounding. In fact, the population generated with person-controls actually slightly outperforms the base procedure in satisfying the household distribution with an average AAPD over all cells of 74% compared to 104% for the POP-HH population. This is possibly due to a more targeted search being performed through the use of the person-level controls and constraints.



(a)



(b)

Figure 6. AAPD Comparison for (a) Household and (b) Person-Level Joint Distribution

The results shown if Figure 6(b) show that, as expected, the fit of the POP-PER synthetic population to the person-level joint distribution is much better than the fit of the POP-HH population, due to the use of the person level controls. The overall AAPD improves from 273% for the POP-HH to 69% for the POP-PER population, which is a significant improvement. The cell AAPD values for the POP-PER population are generally much closer to the expected rounding error, while large differences can be seen in the POP-HH AAPD. It should be noted that while the POP-PER AAPD values also generally follow the expected pattern of decreasing error with increasing average cell size, this is not the case with the uncontrolled population, with large errors seen even for several cells with large average sizes, which reinforces the problem with not controlling for person level characteristics. This result is not merely due to the error caused by large variances in the household size between zones as this is accounted for in the calculation of the expected AAPD value.

Overall, the validation analyses presented in Figure 5 and Figure 6 show that the additional use of person-level controls when generating a synthetic population improve the fit of the resulting population to known person-level characteristics when compared to the same synthetic population generated without person-level controls. The increase in fit to the person-level known marginal totals and estimated joint-distribution is very substantial, with little to no sacrifice in the ability to match household level characteristics. In fact, the ability to match the household joint-distribution is somewhat improved through the use of the person-level controls.

A final validation exercise was performed to determine if the new, more-efficient selection procedure outlined in Section 7.3 had any negative impact on the fit of the synthetic populations, when compared to the traditional selection procedure. Note that for this validation analysis the selection procedure refers only to the manner in which the sample households are searched, both procedures tested here still use the new household selection probability calculation which accounts for person-level characteristics. Also, since the test is conducted to determine the validity of the selection procedure rather than the overall synthesis procedure, the marginal constraints were turned off when generating the test synthetic populations. Three different synthetic populations were generated for 46 block groups within PUMAs 3408, 3409, 3518 and 3519 in the Chicago region which had no group quarters population and minimal discrepancies between household-size counts and population levels. The three populations were: person-level control under the new selection procedure (PER-NEW), person-level control under the traditional selection procedure (PER-OLD) and no person control (PER-NONE).

To test for potential biases in the new selection procedure, the Freeman-Tukey test statistic was used to compare the fit of the generated household and person joint-distributions to the expected distributions from the IPF for each procedure. The advantages of this statistic for use in analyzing goodness-of-fit for synthetic population have been described in Voas and Williamson (2001) and Ryan et al. (2009). The test statistic is calculated as:

$$FT^2 = 4\sum_{i}^{N_{cells}}\sum_{j}^{N_{zones}}(\sqrt{\hat{u}_{ij}} - \sqrt{u_{ij}})^2 \qquad (4)$$

$$FT^2 \sim \chi^2(N_{cells} \times N_{zones} - 1)$$

The statistic is four times the sum of the square of the differences between the square root of actual (u_{ij}) and estimated ($\hat{u}_{ij}$) frequencies over all cells i and zones j, and has a chi-square distribution. The test statistic is calculated and compared to a critical value for a given significance level from the χ^2 distribution to evaluate the fit of the synthesized population to the person-level joint distribution. The results for all three synthetic populations are shown in Table 2 for both the household and person-level distributions at a significance level of 0.05.

TABLE II
SYNTHETIC POPULATION FIT FOR DIFFERENT SELECTION PROCEDURES

	Household-Level Distribution[1,3]			**Person-Level Distribution[2,3]**		
Population	**Crit Val.**	**FT^2 (σ)**	**H_0[4]**	**Crit Val.**	**FT^2 (σ)**	**H_0[4]**
PER-NONE	26,134	4,799 (54)	Accept	5,319	24,786 (434)	Reject
PER-OLD	26,134	5,734 (68)	Accept	5,319	4,044 (106)	Accept
PER-NEW	26,134	6,651 (82)	Accept	5,319	4,840 (102)	Accept

1. 25,759 degrees-of-freedom for household-level distribution.
2. 5,151 degrees-of-freedom for person-level distribution.
3. FT^2 values averaged over 20 runs, standard deviation of FT^2 value shown in parentheses.
4. Null hypothesis accepted if FT^2 is less than critical value at significance level of 0.05, i.e. probability of observir

According to TABLE II the null hypothesis for the Freeman-Tukey test, i.e. the synthesized joint distribution and joint distribution resulting from IPF at the person level have the same distribution, is accepted for both populations with person-level controls and rejected for the population without controls, while the household-level distribution is matched for all populations. The results in Table 2 clearly show that using person-level controls improves the fit of the synthesized person-level joint distribution to the estimated distribution, while not controlling for person-level characteristics results in poor fit to the estimated distribution, as expected. More importantly, the good fit to the joint-distribution is obtained for both selection procedures. While the fit obtained by using the new procedure is slightly worse than using the traditional procedure, it is still good and results in a run-time of 0.7 minutes to synthesize the 85,590 individuals in the example above as compared to 18.6 minutes using the other procedure. The run-time for synthesizing the entire population in the Chicago region using the traditional procedure assuming the same rates obtained above would be approximately 30 hours for a single run compared to the 1.4 hours achieved using the new procedure. The long run times using the traditional selection procedure combined with the potential need for running multiple different permutations of a synthetic population and for averaging over multiple runs for the same population motivates the use the more efficient selection procedure, although the traditional selection procedure can still be used to generate a final synthetic population in combination with initial testing and development done using the faster procedure. For this reason, both selection procedures are implemented in the actual synthesis program with the choice left to the user.

7.5. Computational Performance

Beyond validating the accuracy of the new methodology, it is necessary to evaluate its computational performance. To determine the performance characteristics of the new algorithm, the run times for generating the synthetic populations described in the previous section, POP-HH and POP-PER were compared with run times for generating the full Chicago population with and without person-level controls. The same program settings, other than the use of person control, were used in each run. Each synthetic population was generated by running the population synthesis program on an Intel Centrino Duo 2.0 GHz processor.

The non-person controlled population, POP-HH, which contained 1,500,308 synthetic individuals, took 13 minutes to generate. In contrast, the population with person-level controls, POP-PER, with 1,487,815 people, took over 28 minutes. For the full populations, the non-person controlled full population took about 33 minutes to generate 7,972,057 individuals, while the person-controlled full population took 84 minutes to generate 7,889,221, out of a total actual population of 8,091,720. All of the synthetic populations had a household-level joint distribution size of 560 cells and a person-level joint distribution size of 112 cells.

While it is difficult to compare results across different synthesizers, these run times appear to compare favorably as far as the author can tell. During the validation of the Atlanta Regional Council population synthesizer, a synthetic population of 1.35 million households controlled only at the household level was run in 17.4 minutes with a household-distribution size of 316 cells (Bowman and Rousseau, 2006), about half the time it took to synthesize the 2.9 million households in the Chicago region using only household controls in the new synthesizer.

The only comparable results available for synthesizers which control for person level characteristics were presented in Ye et al (2009) for a synthetic population of 2.9 million individuals in Maricopa County, Arizona. This synthetic population was generated using a household-distribution size of 280 cells (over 3 control variables) and a person-joint-distribution size of 140 cells (over the same three control variables used in this study but with two additional age categories). The overall runtime was 16 hours, longer than the 1.4 hours to generate the Chicago population of 7.9 million individuals with approximately the same number of control variables and distribution matrix sizes.

Population synthesis represents the first stage in the overall activity-based modeling framework. This procedure provides the agents used within the microsimulation and provides them household and person level demographic characteristics and home locations. This information, combined with more general information describing the simulated environment, including network information, land-use data, etc. is used in all of the subsequent stages of the ADAPTS activity based model. The first step within the actual activity-based model stream itself is the generation of new activities for the synthesized agents. This process is described in the next section.

8. ACTIVITY GENERATION

8.1. Introduction and Literature Review

This section of the thesis describes the activity generation process followed in the ADAPTS model. Many operational rule-based models make simplifying assumptions about the scheduling process, with activities basically filling in gaps in a predefined "skeletal" schedule where time permits (Arentze and Timmermans, 2000; Pendyala et al. 2005; Angraini et al. 2007). Recent work has focused on stand-alone theories of activity generation. Habib and Miller (2007) tried to account for day-to-day variation and history dependence using a utility-maximization model. Meanwhile Timmermans and Arentze (2006) have proposed and refined (Arentze and Timmermans, 2007; Arentze and Timmermans, 2009) a "need-based" activity generation model, where individuals have baseline preferences for certain activities which change over time according to the need for completing the activity; another attempt to incorporate dynamics and history dependence in activity generation. Some activity-based modeling systems have even attempted to represent aspects of the scheduling process itself, including activity rescheduling decisions and random activity generation (Roorda et al. 2005a; Joh et al. 2002).

One potential method of accounting for the dynamics of activity generation is through the use of a hazard-duration model, which can be used to estimate the inter-activity occurrence time, i.e. the time between one observation of an activity of a specific type and its next occurrence. The basic development of duration models as an analysis of exponentially distributed life-times was introduced in 1959 by Cox (1959). He generalized his study on life-time data in 1972 (Cox, 1972). In this paper, he proposed a method for analysis of censored failure times. Generally, duration models estimate the elapsed time between two failures, but when the last failure is unobserved it is only known that the time to failure is greater than the censored time, complicating the analysis. Cox's methodology for analyzing failure rates has been applied in many different areas such as medical statistics, epidemiology, economics, and political science studies. Although there are some concerns about these parametric hazard-based models (Abrevaya and Hausman, 1999; Meyer, 1990), these models are still well-known and widely used (Abbring and Van den Berg, 2007).

Applications of hazard-based duration models in the transportation field are emerging. During the early 1990s, basic parametric hazard models with Weibull baseline hazards were employed in several transportation studies (see for example: Hamed and Mannering, 1993; Mannering et al. 1994; Hensher and Mannering, 1994). Later, several activity based models were developed by using either the basic proportional hazard models or advanced hazard-based models (e.g., Abdel et al. 1995; Ettema and Timmermans, 1997). Ettema et al. (1995) presented a competing accelerated hazard model, for jointly modeling duration of the present activity and choice of the next activity. Si milarly, Popkowski et al. (2002) introduced a conditional competing duration model for activities conducted by an individual. In the last decade, activity-based models components have been developed which utilize various applications of parametric hazard models, either proportional or accelerated, with alternative baseline hazards assumptions (Leszcyc and Timmermans, 2002; Ettema et al., 2007). These model applications include using latent class accelerated hazard models and competing hazard-based models (Srinivasan and Bhat, 2005; Lee and Timmermans, 2007).

The work presented in this chapter represents a methodology for using the UTRACS data on activity scheduling, discussed in Part II of the thesis, to estimate a competing hazard activity generation model. The model is then implemented as the activity generation component in the ADAPTS activity-based model. The activity generation model has been estimated for the Chicago region, where activity counts and the inter-activity times are simulated and compared to the observed data to show that the model is functioning as expected and can be used in the activity-generation simulation process. The remainder of the chapter discusses the development of the competing hazard framework, the modeling results and the validation performed to ensure the model is functioning correctly.

8.2. Competing Hazard Model Specification

The focus of this section i s on the development of a competing hazard model of the inter-activity-occurrence duration for a set of discretionary activities. The proportional hazard model formulation, which forms the basis of this work, consists of a baseline hazard and covariates. The parametric proportional hazard can be formulated as:

$$h_i(t) = \lim_{\Delta t \to o} \frac{\Pr(t + \Delta t \geq T \geq t \mid T \geq t)}{\Delta t} = h_{i0}(t) \times \exp(-\beta x_i) = f_i(t) / (1 - F_i(t)) = f_i(t) / S_i(t) \tag{5}$$

where $h_i(t)$ is the probability of failure at time t for individual i given that it has survived until time T and the hazard probability is formulated as a function of covariates (x_i) that can influence the outcome. In this work the hazard is the instantaneous probability of generating an activity of a certain type at time t where t is the time since the last observation of that activity type. Moreover, $h_{i0}(t)$ is considered as the baseline hazard, β is the vector of parameters to be estimated, $f_i(t)$ is the probability density function, $F_i(t)$ is the cumulative density function and $S_i(t)$is the survival function. Equation 5 may be rewritten using a Weibull baseline hazard function as:

$$h_i(t) = \gamma \ t^{\ \gamma -1} \exp(-\beta_x X_i) \tag{6}$$

where γ is the shape parameter of the Weibull distribution, X denotes explanatory variables, and β_x is the vector of parameters. However, this Weibull baseline hazard gives a monotonic failure rate over time; i.e. the hazard is decreasing with time if γ is less than one and increasing if γ is greater than one. This distribution may not best describe the underlying activity generation process, as it seems likely that activity generation is actually a result of several different generation mechanisms. For example during activity scheduling there is likely to be significant impacts due to trip chaining on generating new activities, especially for impulsive activities. This can be thought of as the "Well, I'm already out…" reason for generating new activities. An alternative mechanism would be based more on the growth of need for a specific activity type over time, or the "It's been awhile since…" reasoning. These would correspond to the early failure or "infant mortality" and late failure or "aging" processes in survival analysis. Therefore it seems likely that an alternate specification of the hazard function is needed. For this reason the additive Weibull distribution was chosen for the hazard function. This distribution is the combination of two separate Weibull distributions restricted so that one has a γ value of less than one and the other is greater than one (Xie and Lai, 1995). This distribution is formulated with separate shape parameters γ_E and γ_l and constants C_E and C_L for the early and late failure components respectively, as seen in Equation 7.

$$h_0^i(t) = \exp(-C_E)\gamma_E t^{\gamma_E - 1} + \exp(-C_L)\gamma_L t^{\gamma_L - 1} \tag{7}$$

The survival function which is defined as the probability of surviving an event until it fails at time T, is formulated as:

$$S(t) = \exp\left[-\int_0^t h(u)du\right] \tag{8}$$

Note that in this study, survival is defined as not generating a new activity while when a new activity of a certain type is generated a failure is said to occur. Therefore the survival time is the amount of time since the last observation of the activity type, while the failure time is the survival time at failure. The probability of observing an activity of any kind at time T conditional on not observing it until time T can be formulated using Equation 6. For each activity type, independent hazards with no-endogenous variable (h^{nev}) are initially estimated as shown in Equation 9.

$$\begin{cases} h_i^{nev}(t_i, x_i) = h_0^i \, e^{-\beta_i x_i} \\ h_k^{nev}(t_k, x_k) = h_0^k \, e^{-\beta_k x_k} \\ h_j^{nev}(t_j, x_j) = h_0^j e^{-\beta_j x_j} \\ \quad \vdots \end{cases} \tag{9}$$

where h_i^{nev}, h_j^{nev} and h_k^{nev} stand for the hazard function of activities i, j and k with only exogenous variables, β_i, β_j and β_k are covariate coefficient vectors, γ_i, γ_j and γ_k are baseline hazard scale and shape parameters.

Intuitively, different activity types do not occur independently from each other and this dependency should be included in the modeling formulation. For example, the generation hazard of a maintenance activity can influence the probability of generating a mandatory or a discretionary activity. In order to incorporate these dependencies between the activities, the impact of occurrence of any activity j at time T on another activity i is included in the hazard function of activity i. In other words, the hazard function value of any activity j with no-endogenous variable, as shown in Equation 9, which is influenced by the baseline hazard function and some covariates in the exponential function, is added to the covariates that are used for estimating the hazard value of activity i. This can result in estimating hazard functions with endogenous variables (h^{wev}). Equation 10 presents an example of such equations where activity types i, j, k, etc influence each other:

$$\begin{cases} h_i^{wev}(t_i, x_i, h_j^{nev}, h_k^{nev}, \ldots) = h_0^i \, e^{-(\beta_i x_i + \beta_{ji} h_j^{nev} + \beta_{ki} h_k^{nev} + \ldots)} \\ h_j^{wev}(t_j, x_j, h_i^{nev}, h_k^{nev}, \ldots) = h_0^k \, e^{-(\beta_k x_k + \beta_{ij} h_i^{nev} + \beta_{kj} h_k^{nev} + \ldots)} \\ h_k^{wev}(t_k, x_k, h_i^{nev}, h_j^{nev}, \ldots) = h_0^k \, e^{-(\beta_k x_k + \beta_{ik} h_i^{nev} + \beta_{jk} h_j^{nev} + \ldots)} \\ \quad \vdots \end{cases} \tag{10}$$

where β_{ji} represents the impact of the hazard values of activities j on activity i and similary for other activity cases. Note that the hazards are dependent on the variable t_i (or t_l, t_k, etc.), which is defined as the current inter-activity duration (or time since last occurrence) for activity type i at time T. Equation 10 can be easily expanded to m activity types while for each activity the impact of the other $(m\text{-}1)$ activity types can be included in the formulation. Using the hazard functions of Equation 10 the likelihood function which is used for estimating the parameters of the models can be written as:

$$L = \prod_{i=1}^{N} \prod_{j=1}^{M} [h_{ij}(t) \times S_{ij}(t)]^{y_{ij}} \tag{11}$$

where N is the number of observations, M is the total number of activities considered, y_{ij} is equal to one if activity type j occurred and zero otherwise and $S_{ij}(t)$ stands for the survival function which is calculated using Equation 8. Next, the use of the UTRACS survey data in estimating the competing hazards model is discussed.

8.3. Use of UTRACS Data in Activity Generation Modeling

In order to estimate the competing hazard model of inter-activity durations, which is to be used as the activity generator for the ADAPTS model, a source of data which captures activity engagement for individuals over long time periods was required. The standard one or two day activity diary surveys do not provide enough data on the inter-activity durations as such data is too highly censored. In other words we need data over a long-enough time period so that multiple observations of each activity type are made giving sufficient information about the timing between the activities. Therefore it was decided for this work to use the data collected in the UTRACS survey, detailed in Part II of this thesis.

The UTRACS survey was a GPS-based prompted recall activity-travel survey that collected data regarding respondents activity planning and activity attribute flexibilities over long time periods. The activity data recorded in UTRACS were collected and filtered to exclude individuals who had large unexplained gaps in their activity records (not caused by non-mobility) and who did not complete the survey for at least 5 days, as such data would be likely to significantly bias the duration results. Overall data on 1466 non-routine, out-of-home activities from 75 respondents were used in the model estimation.

8.4. Competing Hazard Activity Generation Model Results

The next step in creating the competing hazard activity generation model involved using the above described data to estimate the model parameters. The nonlinear programming method in the SAS statistical software package was employed to estimate the unknown parameters such that they maximized the likelihood function presented in Equation 11. The variables that were used in the model include: the number of workers, students, children, vehicles, and individuals in the household. There were also eight indicator variables indicating whether each individual is: male, a student, a senior, married, disabled, employed, a frequent internet user, occasional teleworker; or has: cell phone, driver license, or college degree. Three more dummy variables were dedicated to household socioeconomic situation: whether the household is low-income (<35,000 per year), medium-income (between \$35,000 and \$75,000 per year), hi-income (>\$75,000 per year), and whether they live in a single family house. The averages of the variables that were found significant in the model, as well as the dependent variables (inter-activity durations measured in days) are shown in TABLE III. An additional set of variables not shown were the employment accessibility variables which serve as a proxy for activity opportunities. These variables are gravity model based using fitted network skim data. The calculation of these variables is discussed in Section 10.2

TABLE III
MODELING VARIABLE AVERAGE VALUES

	Shop	Service	Health	Person.	Errand	Eat Out	Relig.	Leisure	Social	Total
Observations	640	60	56	116	66	157	72	146	153	1466
Dependent Var.										
Failure Time (days)	1 69	7 20	9 35	3 90	7 47	4 09	9 53	3 68	2 54	3 57
Continuous Var.										
HH Size	2 37	2 07	2 11	2 18	2 42	2 15	1 83	2 22	2 46	2 28
Num Students	0 52	0 52	0 32	0 39	0 59	0 41	0 33	0 58	0 65	0 50
Num Children	0 42	0 25	0 25	0 20	0 48	0 20	0 18	0 29	0 39	0 34
Num Vehicles	1 90	1 72	1 70	1 90	2 05	1 93	1 53	1 78	2 07	1 88
Indicators (1=yes)										
Med Income	0 32	0 32	0 23	0 28	0 44	0 29	0 42	0 31	0 33	0 32
High Income	0 36	0 27	0 38	0 29	0 29	0 37	0 25	0 42	0 39	0 35
Married	0 77	0 60	0 66	0 75	0 83	0 71	0 64	0 66	0 77	0 74
Own House	0 83	0 65	0 71	0 81	0 86	0 75	0 61	0 70	0 82	0 78
Senior	0 63	0 53	0 71	0 72	0 68	0 73	0 67	0 60	0 58	0 64
Male	0 37	0 30	0 25	0 54	0 58	0 33	0 39	0 45	0 40	0 39
Disabled	0 23	0 28	0 43	0 19	0 30	0 28	0 40	0 36	0 22	0 26
Employed	0 93	0 85	0 95	0 95	0 95	0 97	0 93	0 92	0 94	0 93
Student	0 08	0 07	0 09	0 16	0 11	0 08	0 17	0 16	0 10	0 10
Has Degree	0 62	0 58	0 64	0 66	0 47	0 66	0 61	0 74	0 66	0 64

Maximizing the likelihood function of the competing hazard model presented in Equation 11 while accounting for the competition between activities, produced a set of parameter estimates which model the observed inter-activity failure time Several different versions of the model have been developed for comparison purposes, including a model with simple monotonic Weibull baseline hazard functions, a version with additive hazard functions but no accessibility measures and the final model shown in Equation 10, which includes both additive weibull hazard functions and accessibility measures for activity generation The final model fit results for each version of the model, as well as the null model are shown in TABLE IV As can be seen in the table the final competing hazards activity generation model has an acceptable fit to the observed data, with a significant improvement in the log likelihood value at convergence, with a likelihood-ratio index of 0 167 The final model outperforms the various other models in terms of the likelihood ratio as well as the AIC and BIC measures which take into account the number of parameters in each model at levels generally regarded as highly substantial

TABLE IV
ACTIVITY GENERATION MODEL FIT MEASURES

Model	LL	ρ	N	k	AIC	BIC
Null	-2627.7	–	0	1466	5255.5	5255.5
Basic Weibull	-2398.6	0.087	56	1466	4909.2	5205.5
Additive Weibull	-2251.8	0.143	72	1466	4647.6	5028.5
Additive w/accessibility	-2189.9	0.167	77	1466	4533.8	4941.2

The parameter estimates for the final model are shown in TABLE V. After testing each variable during model estimation, those which were significant at 95% confidence interval were kept in the model and others were eliminated including the endogenous factors that were not significant. It should be noted that a negative sign for each parameter indicates an increase in the hazard of occurring for an activity, which reduces the survival time. Therefore negative parameters cause activities to occur more frequently and vice versa.

Most activities in the model exhibit the expected "bathtub curve" shape for the baseline hazards, with high initial hazards decreasing rapidly with time – indicative of trip-chaining – and a gradually increasing hazard as time goes on. The only activity which deviates from this pattern is the social activity in which only the early failure parameters were significant. The values of the various additive Weibull parameters produce substantially different shapes of the baseline hazard curves for the various activities. The healthcare, personal and to a greater extent the service activities both display increasingly rapid hazard growth over time, indicating more and more need to engage in these activities as the time since the last activity grows. The 'eat out' activity also shows somewhat strong growth over time, though at a decelerating rate, and also a small effect from the early life parameters, indicating a low trip-chaining propensity. The baseline hazard distributions for each activity type are shown in Figure 7. Note that in the figure, the hazard value axis is limited to a maximum value of 1.0 so that all curves can be seen.

TABLE V
ACTIVITY GENERATION MODEL ESTIMATION RESULTS

Parameter	Estimate	t-stat
Shopping		
Gamma_L	1 08	8 8
Gamma_E	0 48	18 4
Const_L	1 74	2 6
Const_E	-0 49	-1 9
Med Income	-0 53	-4 59
High Income	-0 42	-4 04
Num Children	-0 14	-3 15
Gov Access	0 03	1 55
Ind Access	0 09	2 82
Retail Access	0 17	4 47
Other Access	-0 32	-3 58
Log (avg time)	0 18	1 83
Service		
Gamma_L	4 86	2 71
Gamma_E	0 32	7 13
Const_L	10 69	2 27
Const_E	-0 73	-1 31
HH Size	0 26	2 43
Gov Access	0 03	3 13
Health		
Gamma_L	3 40	4 86
Gamma_E	0 34	5 69
Const_L	8 52	3 98
Const_E	0 56	1 45
Student	0 63	2 40
Retail Access	0 08	2 29
Personal		
Gamma_L	6 68	10 66
Gamma_E	0 48	12 78
Const_L	18 25	9 30
Const_E	0 23	0 81
Single Fam House	-0 74	-3 33
Ind Access	0 05	2 27
Errands		
Gamma_L	4 36	4 5
Gamma_E	0 43	6 0
Const_L	13 58	4 1
Const_E	2 91	3 3
HH Size	0 58	2 10
Num Children	-0 39	-1 78
Num Vehicle	-0 77	-3 39
Employed	-1 29	-1 69
Gov Access	0 09	1 66
Serv Access	-0 03	-2 13

Parameter	Estimate	t-stat
Eat Out		
Gamma_L	1 16	14 01
Gamma_E	0 21	8 26
Const_L	0 57	1 43
Const_E	0 39	0 93
High Income	-0 68	-4 43
HH Size	0 45	3 15
Num Students	-0 57	-3 14
Male	-0 66	-3 38
Religious		
Gamma_L	4 18	6 59
Gamma_E	0 65	5 99
Const_L	12 58	5 68
Const_E	2 01	6 48
Married	-0 72	-2 51
Num Students	0 32	1 63
Leisure/Recreational		
Gamma_L	1 28	12 5
Gamma_E	0 27	6 4
Const_L	2 66	6 2
Const_E	1 61	4 9
Male	-0 31	-1 85
Employed	0 85	3 53
Degree	-0 51	-3 33
Retail Access	-0 34	-1 92
Social		
Gamma_E	0 53	13 18
Const_E	0 04	0 19
Disabled	0 32	1 91
Other Access	0 05	1 93
Endogenous Factors		
Shop on Service	-0 34	-3 44
Eat-out on Service	0 79	2 15
Religion on Service	3 99	2 37
Eat-out on Personal	0 06	1 50
Religious on Personal	1 82	2 19
Religious on Eat-out	0 68	1 71
Leisure on Eat-out	5 35	2 57
Social on Eat-out	-0 33	-2 27
Personal on Religious	0 25	2 42
Eat-out on Leisure	-0 36	-1 39
Religious on Social	-1 25	-1 53

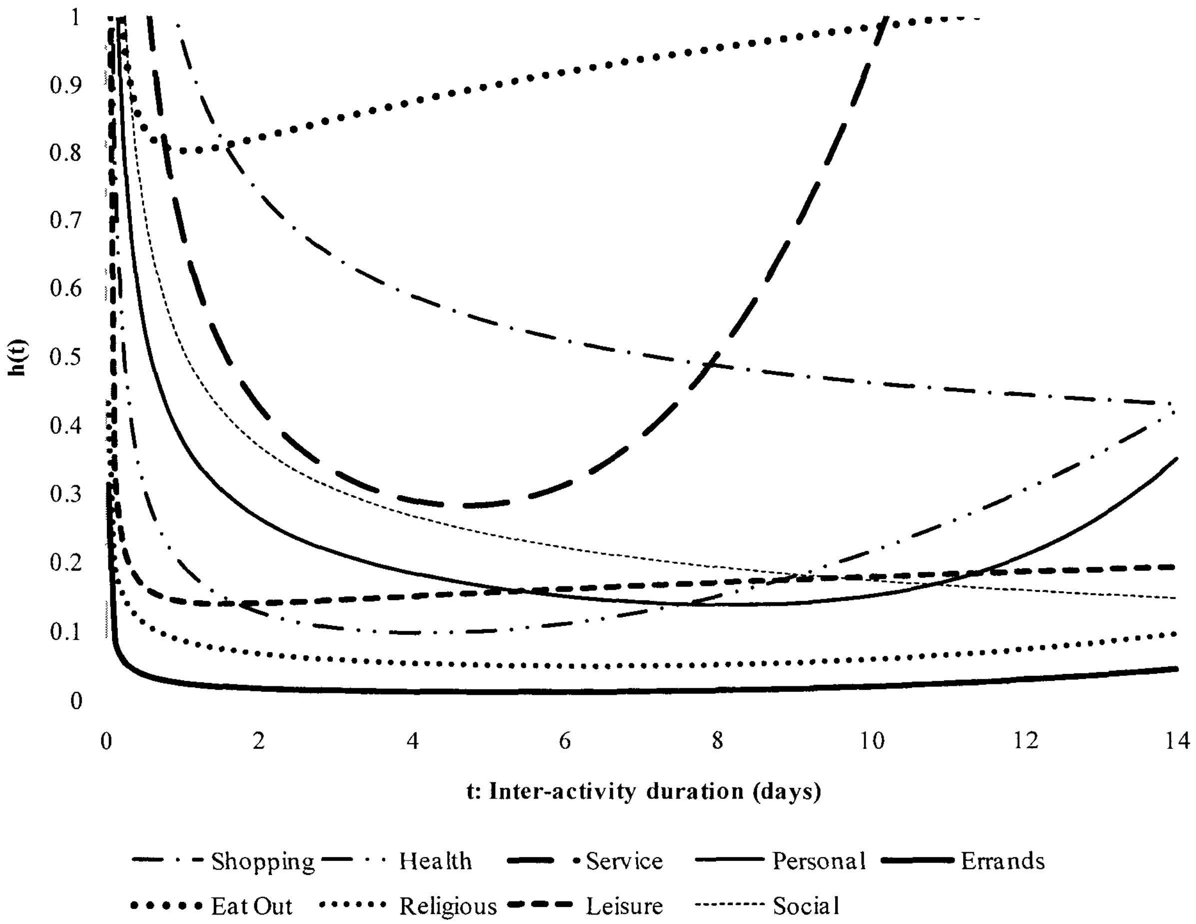


Figure 7. Baseline Hazard Distributions for Activity Generation

The figure shows that the service, personal and healthcare activities exhibit strongly increasing hazard as the between activity time grows, indicating a high needs growth over time for these type of activities as expected. The eat-out activity also indicates a needs growth over time, but at a decelerating rate. Interestingly, several activities, such as the leisure and errands activities, seem to approach a constant hazard rate over time indicating a random generation probability after the initial trip chaining stage is passed. It is important to note, however, that these are baseline hazard curves and are not inclusive of the effects of covariates which can scale them up or down for any individual observation although the hazard functions will always retain the same shape.

In assessing the estimated covariate parameters, the model suggests that the hazard of shopping activities increases when the households are not low income, which means individuals in such households are more likely to shop more frequently than individuals in households with lower incomes The model also shows that individuals in households with more children are more likely to shop more often (the shopping hazard increases), which is intuitive as increasing number of children require the additional procurement of goods and children are generally not tasked with household shopping, which is why this variable is significant in place of the household size As the average travel time to shopping activities increases they become less likely as expected, however, the model shows that individuals in areas more accessible to retail also engage in shopping activities with a lower frequency This last result is likely due to the decreased need to chain shopping activities when plentiful opportunities are nearby, thereby giving a longer observed duration between activities

The model also indicates that being a student, which often means being young, reduces the hazard of healthcare activities as expected Furthermore, according to the model married couples are more likely to engage in religious activities, while individuals in households with more students are less likely to engage in religious trips, perhaps due to less time available to households with school age children

Being male or having a college degree and living in a high retail accessibility area all increase the chance of having more leisure activities, according to the results, while employed individuals are less likely to engage in such trips, which is intuitive as they generally have less discretionary time available In a similar fashion, males and individuals in high-income households or in households with more students are more likely to eat-out while household size has a negative impact on engaging in eat-out activities, as larger households often indicate family households more likely to eat at home together in comparison to single individual households and eating out represents more of an economic burden for larger households

Intuitively the hazard of running errands for employed individuals, and those in households with more cars or more children is higher than individuals in similar households However, the model shows that that the hazard decreases for those who live in larger household sizes as was also found for service activities These could be attributed to the fact that in such households individuals share the responsibilities, hence the average number of errands or service activities for each person decreases as a certain portion of household errand and service activities are required to be done regardless of household size. The estimated parameters also show that the hazard of making social trips is smaller for those who are disabled as would be expected.

The previous discussion relates only to how the exogenous demographic variables relate to the inter-activity time. However, the model also includes many endogenous factors relating to the competition between activities which also significantly affect the results. The estimates of the endogenous parameters show that Eat-out activities delay service and personal activities but increase the hazard for leisure activities, while the need for Social activities also increases the hazard of eat out activities. This shows that discretionary activities and maintenance activities are generally engaged in at separate times; with individuals perhaps fulfilling their obligations and then filling remaining time with discretionary acts. On the other hand, the model shows that the need for making personal trips delays religious activities, while an increase hazard of participating in religious or civic activities generally delays both discretionary and maintenance activities but encouraging socializing, indicating that religious activities are less likely to be engaged in with other activities other than socializing. This represents the traditional pattern of religious activity engagement, with individuals spending the time, generally on weekends, at religious activities then socializing with friends, family or members of the religious community afterwards. Finally, it also appears that shopping and service activities are more likely to occur together as combined maintenance tours In general, the endogenous factors show the competition for time is between discretionary activities done for enjoyment such as eating out, socializing, recreation and religious versus those done more out of obligation or need such as shopping, errands, healthcare, etc.

8.5. Activity Generation Validation Results

After the competing hazard activity generation model was developed, it was implemented within the ADAPTS model activity scheduler, in order to perform validation tests. To determine if the model was functioning correctly, the ADAPTS activity generator was run for 21 days to produce a complete set of generated activities for the individuals in the UTRACS sample. The activity generator was called at every 15-minute time step to determine the generation probability for each activity type. These probabilities were estimated using the above formulation. An important aspect of the simulation is on setting the initial conditions, specifically the survival times for each activity at the start of the simulation. Setting these values to zero or not specifying them causes serious bias in the simulation, as many of the activity types are most likely to occur immediately after the last observation of the activity due to the trip chaining effect. So if each activity starts with a zero survival time the total number of activities would be greatly overestimated. For this reason, random draws from the inverse survival function for each activity were made for every individual to simulate the activity survival times at the start of simulation. The generated activity patterns were evaluated to determine how well they are replicating the observed activity counts and distributions from the UTRACS data. First, the overall average daily activity count for the simulated sample was compared to the observed averages. A total of seven model runs, each producing 21 simulated days, were performed to calculate the average daily activity rate. The results are shown in Figure 8.

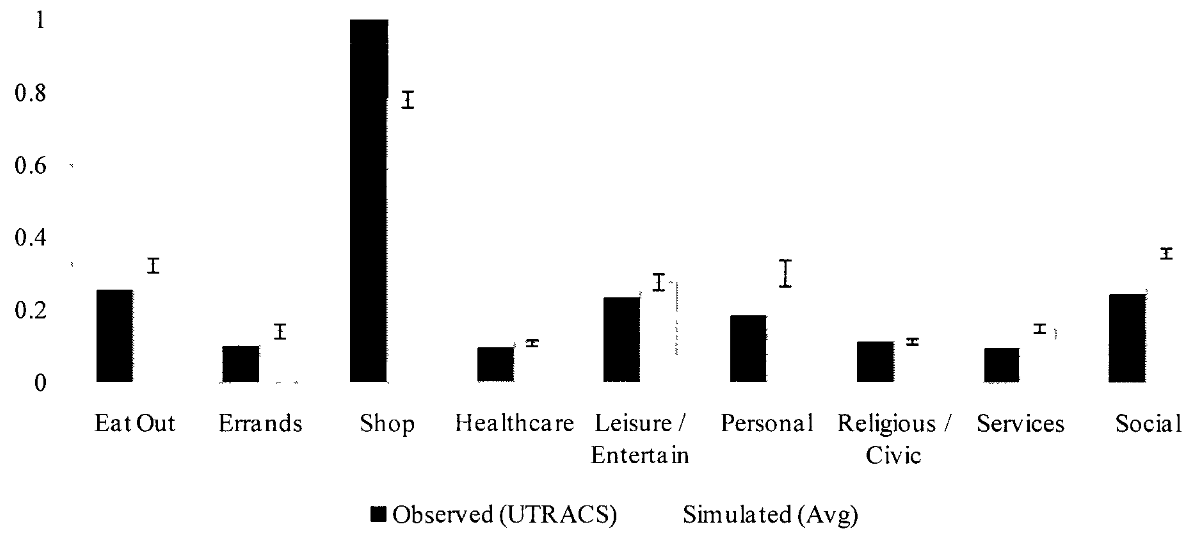


Figure 8. Comparison Between Simulated and UTRACS Daily Activity Rates

The figure shows that in general, the simulated competing hazard activity generation model is performing well. The simulated daily activity rates match those observed in the UTRACS data, with slight underestimation of shopping activities, and overestimation of several other activity types, especially personal and social activities. Overall there was a mean absolute percent error (MAPE) between the simulated and observed activity rates of 35%. However, the primary motivation behind the development of this model was to capture the dynamics of activity generation, so a second validation check was performed to determine how well the model is estimating the inter-activity duration distributions for each activity type. In order to simulate this, the information on the total survival time for each activity is recorded as it is generated, which gives the failure time distribution. This enables the development of simulated survival time distributions calculated from the failure time distributions, which can then be compared to the observed survival time distributions. This comparison is shown in Figure 9 below, for four activity types: eating out, shopping, leisure and social.

These figures show that again, in general, the simulation is accurately replicating the observed data from UTRACS. The shop, leisure and social activity survival curves match very closely to the observed distributions. Most of the mismatch in the shop curve is due to an overestimation of the number of short failure time activities, due to activity chaining, with about 10% more activities in this category in the simulation than observed. A similar pattern is observed for the leisure activity, while the difference for the social activity is mostly due to more activities occurring one day after the prior activity in the simulation than observed. A larger discrepancy is observed for the eating out activity, with many more activities occurring during the same day in the simulation than were seen in the data. This likely accounts for the over-simulation of this type of activity as well. The remaining activity types displayed similar fit characteristics to the observed data.

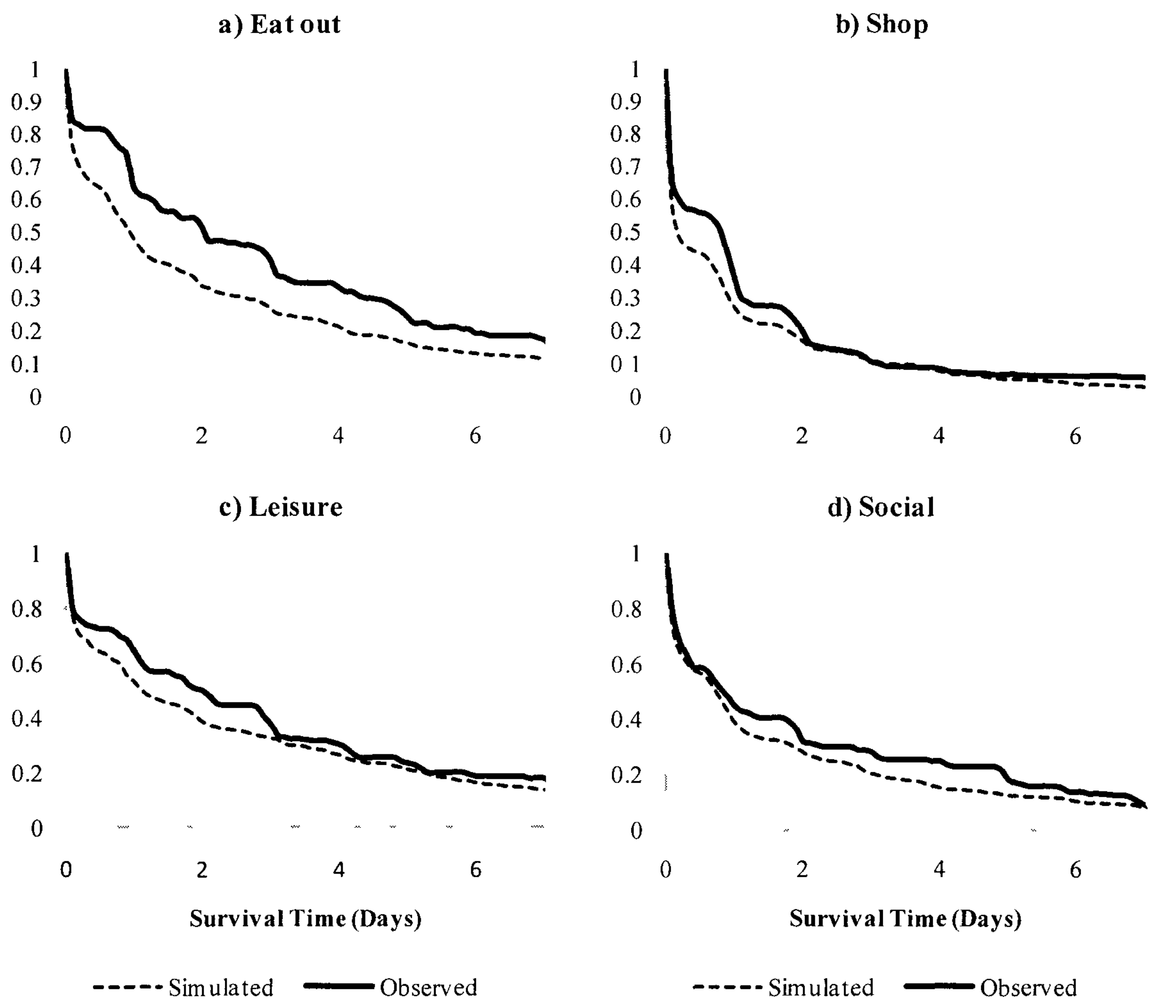


Figure 9. Comparison of Simulated and Observed Activity Survival Time Distributions

8.6. Future Work in Activity Generation

The current analysis is limited due to the small size of the UTRACS sample. Although the survey is shown to be reasonable free from bias, the data only represents 110 individuals and has a high proportion of elderly individuals. The ADAPTS activity generation model formulation used in this study can potentially be improved in several ways. The presented parametric formulation of this study can be substituted with a nonparametric formulation which may result in more consistent parameter estimation although reducing the model estimation efficiency. Additionally, the application of other parametric baseline hazard functions can be informative, as the monotonic Weibull hazard may not be the best representation of the actual activity generation hazard rate. Also, tests to see if the use of accelerated hazard models can provide better compared to the current model can be undertaken. Finally, during the completion of this work it was observed that it would be beneficial if future iterations of long-term household travel surveys would include data on the last occurrence of all activity types of interest prior to the start of the survey for all respondents. This information would help correct for the sometimes significant left-censoring (where the survival time for the first activity observation is not known as it is not observed), which is especially important for some of the more infrequently observed activity types.

The activity generation model presented here is the first primary component of the ADAPTS model framework. It generates basic generic activity episodes which have no individual characteristics pre-determined. Therefore the activity generation stage in ADAPTS represents the most fundamental level of activity planning, which is an approximation of the point in real-life when an individual would say, "I need/want to ___". Examples would include statements such as "I need to go shopping", "I should visit my family", "the car needs an oil change", and so on. The planning of the individual activity attributes and the scheduling of the activity into the final planned activity schedule occur later (although "later" can occasionally be immediately afterwards in the case of "Impulsive" activities. The determination of exactly when the activities are to be planned is discussed in the following chapter.

9. ACTIVITY PLANNING ORDER MODEL

9.1. Introduction

Choice decisions for activity attributes in a typical travel demand model, whether it is the choice to add an activity, the choice of mode, location, etc , can generally be formulated with the probability for any choice as a function of the individual and household demographics, institutional, household and scheduling constraints, land-use patterns, network conditions, etc However, in order to account for scheduling dynamics, a new formulation for choice probability is needed which has two important differences First, the probability is time dependent, i e the probability of making the choice is calculated at a specific time in the simulation as opposed to within a fixed sequential order of schedule construction, so the probability of making a mode choice depends explicitly on when that decision is made, so decisions for the same activity can be different depending on when they are made due to changing constraints, new information, etc Second, in a typical scheduling model, the activity schedule is built up in a sequential manner, typically scheduling around a core of skeletal or routine activities (Roorda et al 2005) This means that schedule constraints are determined based on the timing of the previously planned activity and any routine activities already in the schedule The new formulation explicitly states the choice probability depends on the schedule and existing constraints when the choice is made

The motivation for using a dynamic scheduling process is best exemplified with a planning/scheduling example Consider in Situation A, a person is planning to meet friends for lunch at 1PM She realizes she has some shopping to do, and decides to go shopping at nearby store beforehand In this case, the previously planned activity of eating lunch dictates the planning of the shopping activity Alternative, in Situation B a person is planning to do some shopping in a retail area and decides to call some friends to meet for lunch nearby after her completion of the shopping trip at 1PM Here the already planned shopping trip constrains the choices about the eating out activity The patterns for each situation are shown in Figure 10

In both examples shown, the activity schedule looks identical shopping, then a lunch with friends at a nearby restaurant But in each case, how the schedule was determined was very different Anything altering the planning process could result in an entirely different activity pattern To relate this to potential travel demand management policies, imagine a road pricing regime was put in place which makes the cost of travel such that planning a trip to the store is undesirable, but travel for eating a meal with friends is still desirable. Under this new pricing policy Situation 1 would result in two activities since the shopping trip is in the vicinity of the restaurant, while Situation 2 would result in no activities as the impulsive decision to go to the restaurant would never be made as the initial shopping trip is no longer undertaken. It is critical to note that any model that does not explicitly take into account planning order cannot represent the distinction between Situation A and Situation B, as the only difference lies in the order and degree of impulsiveness with which the activities are planned. In order to understand and model the dynamic planning process new sources of data regarding when activity and activity attribute planning decisions are made are required.

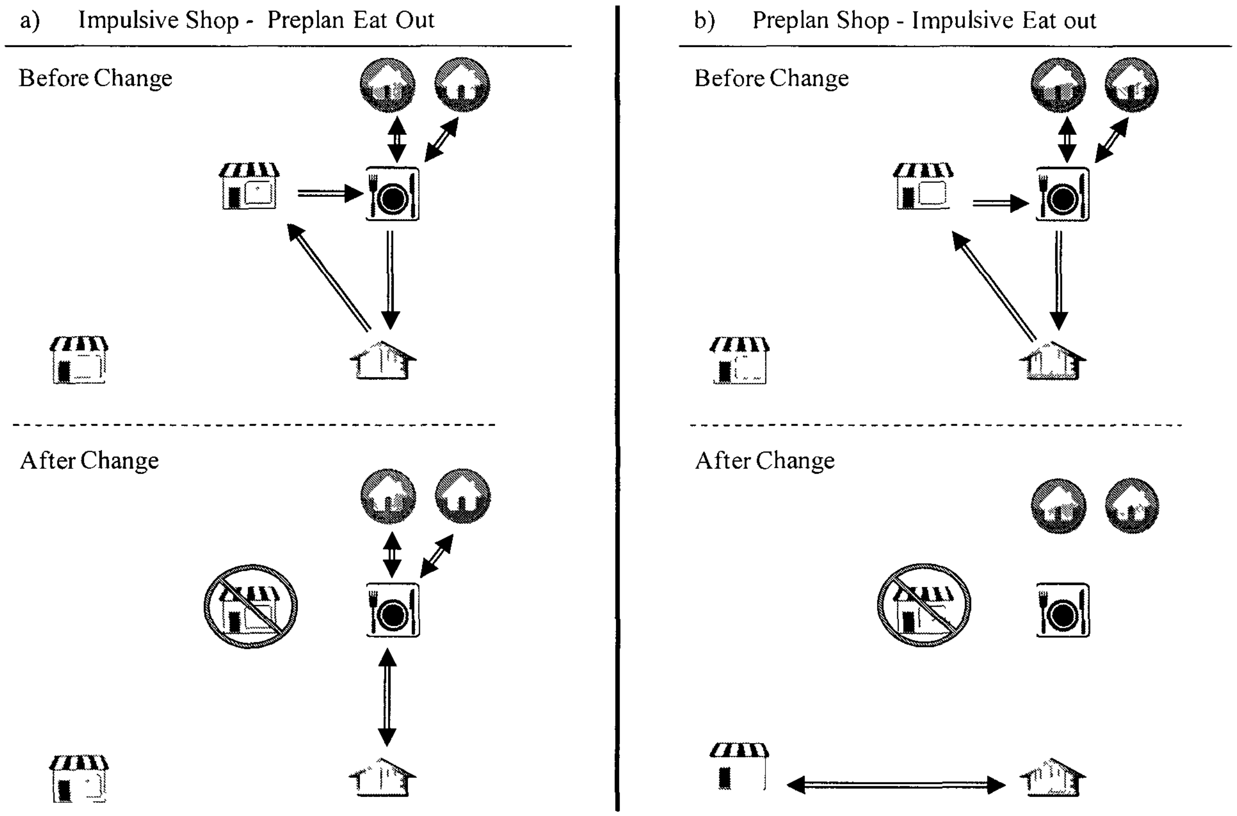


Figure 10. Example of the Impact of Planning Order on Activity Patterns

This section of the thesis is focused on developing the framework for the activity planning model, which allows the activity attributes to be planned in any order Therefore there is no pre-determined planning order assumed in the model Rather the order in which the activity attributes are planned is determined at the time the activity is generated using an attribute planning order model based on personal characteristics, existing schedule characteristics, activity type, space-time constraints, etc

The fundamental concept implemented in the planning order model is the extension of the planning horizon (Doherty 2005) from activity planning to activity attribute planning such that each component attribute of each activity has its own planning horizon The planning order is set by evaluating a plan horizon for each attribute which defines an event at some later time in the simulation for that attribute to be planned This means that an activity can be generated at a given time, and each attribute of the newly generated activity would be chosen at some future times Each attribute decision would then depend on the current state of the individual and schedule at the time it is made as well as all previous attributes of the activity that have already been determined This gives a fully dynamic time-dependent planning model incorporating dynamic scheduling constraints and even potential random events or changes to the schedule The incorporation of dynamics into activity planning and scheduling and removing the fixed planning order assumption for activity planning should allow for a more realistic and policy sensitive microsimulation model

In this section, the various components of the planning order model that are implemented in the overall simulation framework are discussed The data results from the UTRACS GPS-based prompted recall are again used to estimate the various models, and are briefly discussed in the context of the planning order model The rest of this chapter is structured as follows First the planning order framework within the overall planning framework is presented, and the modeling methodology is introduced The use of UTRACS as a data source is briefly discussed, and the model results and validation are documented The section concludes with a discussion of the planning order model, the results obtained and its overall use within the ADAPTS framework

9.2. Framework for Activity Attribute Planning Order Model

As discussed in the previous section, the activity planning order model is implemented immediately following the generation of any new activity within the overall ADAPTS planning framework shown in Figure 3, and occurs under the general heading of "Activity Generation". This is due to the fact that the planning order model sets what are considered in the ADAPTS framework to be intrinsic attributes of the activity such as the location, who-with, start time, etc. flexibilities, the activity planning horizon, and the attribute plan horizons, which are acted on in later stages, and usually at later timesteps, in the planning and scheduling framework. This section, then, discusses how these intrinsic characteristics beyond the activity type are set for the newly generated activity (as discussed in the previous section) to enable later attribute planning. There has been some consideration of the idea that such models may even be able to eventually replace the traditional generation of specific activity types, i.e. instead of generating a "work" activity a "long-average duration, fixed-location, fixed-time, routine" activity could be generated (Doherty 2006), although this approach has not been entirely adopted in the ADAPTS framework as activities of a specific type are still generated.

A more detailed diagram of the general "Activity Planning Order model" or "Plan Order" step of the ADAPTS framework is shown in Figure 11. The "Generate New Activity" step is shown in the diagram for clarity although it is in actuality a preceding step to the Plan Order model within the overall framework. This stage of the framework is referred to as the "Activity Planning Order model" because it defines the order and timing within the simulation when the various attribute decisions are made, in addition to other important activity attributes such as the overall activity planning horizon "Plan Activity" and the various flexibility measures. The final output of this stage is the attribute plan horizons, i.e. "plan person", "plan location", etc. which are used in the following step of the ADAPTS framework to set the attribute planning flags in the simulation as shown in Figure 3, as well as the attribute fixities which can be used to constrain later decisions.

Figure 11 shows that several models are needed in order to complete the "Plan Order" step. These include a model for the activity attribute flexibilities, a model of the overall activity planning horizon and a model for the individual attribute planning horizons. The outputs estimated for each model are expected to be used as conditioning variables for the models which follow, so that the flexibility results are determined solely based on activity type and personal characteristics, while the results of this model feed into the activity plan horizon model which follows. The flexibility and plan horizon results are then both used within the attribute plan horizon model, which determines the final planning order for the attributes. Due to the expected high correlations between responses for individual attributes, both the flexibility and attribute plan horizon models are estimated as multivariate probit models, discussed in the following section, while the overall activity plan horizon model is formulated as a standard univariate ordered probit model.

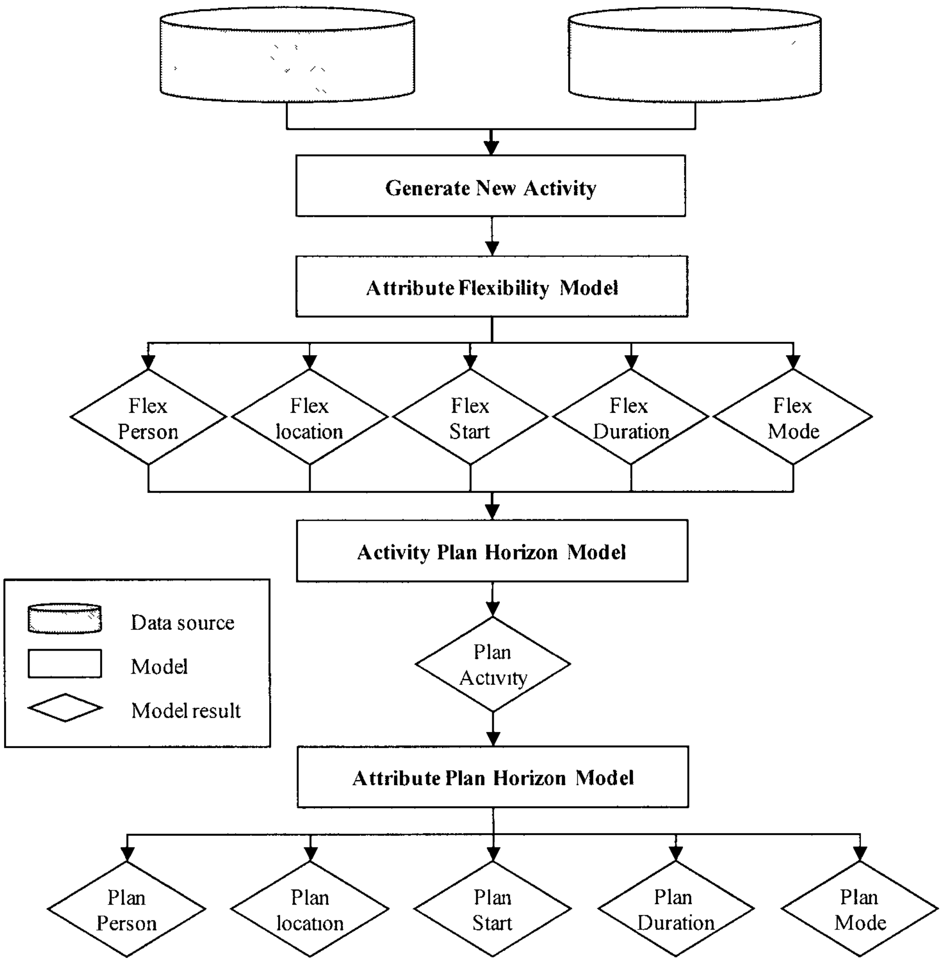


Figure 11. Detailed Diagram of Non-routine Activity "Attribute Planning Order Model"

9.3. Univariate and Multivariate Ordinal Probit Modeling

The dependent variables in the models to be estimated are binary and ordinal measures of the degree of flexibility and preplanning for various activity attributes, respectively as well as an ordinal measure of the overall activity plan horizon. The response values range from "impulsively planned" to "planned over a week ago" to "routine" for the plan horizon responses and "inflexible" or "flexible" for the flexibility responses, indicating the use of an ordinal response model for the plan horizons and a binary response model for the flexibilities. In addition, the flexibility and attribute plan horizon models account for multiple responses –for mode, party composition, location, start time and duration choices – made on the same unit of analysis, which is a single activity observation. This is the common situation – multiple responses obtained from the same observation unit – in which correlated responses arise, potentially indicating the use of a multivariate model. The likelihood is high that unobserved factors on each observation about how a mode, location, etc. choices are made are related to the unobserved impacts on the other choices for the same activity observation, potentially giving rise to the cross-response correlations. Multivariate Probit models are a type of model capable of representing these correlations.

The Ordered Probit model is an extension of the basic probit model for binary responses extended to ordinal responses (Zavoina and McElvey 1975). In the univariate Ordered Probit model, discrete values of the ordinal response Y_i having values 1, 2...K are for each individual i are observed. It is assumed then that there is an underlying latent variable $y^*_i = x_i\beta + \varepsilon$ which, along with a set of threshold-values α_k for (k = 1, 2,...K-1), determine the discrete value by:

$$Y_i = k, \text{ if } \alpha_{k-1} < y^*_i \leq \alpha_k, \text{ where } (\alpha_0 = -\infty \text{ and } \alpha_K = \infty) \tag{12}$$

When the error term on the latent variable ε, is assumed to be distributed with the standard normal distribution, this produces the Ordered Probit model as follows, where Φ is the standard cumulative normal distribution function:

$$
\begin{aligned}
P(Y_i = k) &= P(y_i^* \le \alpha_k) - P(y_i^* \le \alpha_{k-1}) \\
P(Y_i = k) &= P(x_i\beta + \varepsilon_i \le \alpha_k) - P(x_i\beta + \varepsilon_i \le \alpha_{k-1}) \\
P(Y_i = k) &= P(\varepsilon_i \le \alpha_k - x_i\beta) - P(\varepsilon_i \le \alpha_{k-1} - x_i\beta) \\
P(Y_i = k) &= \int_{-\infty}^{\alpha_k - x_i\beta} \phi(x)dx - \int_{-\infty}^{\alpha_{k-1} - x_i\beta} \phi(x)dx \\
P(Y_i = k) &= \Phi(\alpha_k - x_i\beta) - \Phi(\alpha_{k-1} - x_i\beta)
\end{aligned}
\tag{13}
$$

In the extension of the Ordered Probit model to the Multivariate Ordered Probit (MVOP) model, first described for binary responses by Ashford and Sowden (1970), there are multiple observed ordinal response observations Y_{ij} for responses $j = 0, 1, \ldots J$, with K_j discrete outcomes for each response, and the error terms in the latent variables for each response are distributed multivariate normal, $\varepsilon_j \sim N(0,\Sigma)$. The error terms in the latent variables thus have a standard multivariate normal distribution where Σ is the covariance matrix between the various responses. The Multivariate Ordered Probit model can then be written as:

$$
Y_{ij} = k, \text{ if } \alpha_{j,k-1} < x_{ij}\beta_j + e_{ij} \le \alpha_{j,k}, \text{ where } (\alpha_{j,0} = -\infty \text{ and } \alpha_{j,K_j} = \infty) \tag{14}
$$

In the bivariate case, for example, manipulations similar to that shown in Equation 13 leads to the joint probability of the first response having categorical value m and the second response have the categorical value n (dropping the individual subscript i):

$$
P(Y_1 = m,\ Y_2 = n) = \int_{\alpha_{1\,m-1} - x_1\beta_1}^{\alpha_{1\,m} - x_1\beta_1} \int_{\alpha_{2\,n-1} - x_2\beta_2}^{\alpha_{2\,n} - x_2\beta_2} \phi(x_1, x_2)dx_2 dx_1 \tag{15}
$$

The probability defined above can be used to define the likelihood function for the observed data and the parameters estimated through approximate solution methods (Fu et al 2000, Li and Schafer 2008). The use of this formulation for developing the model of the activity attribute planning horizons increases the efficiency of the parameter estimates by accounting for the correlation between the responses as compared to developing individual ordinal models for each response, much in the way that a seemingly unrelated regression (SUR) model (Zellner 1962) does for a linear system. Multivariate probit models are used to model both the flexibility and attribute plan horizon responses, while a univariate ordered probit model is used to model the overall activity plan horizon.

Models of this type have been used to estimate various transportation related topics, for example Choo and Mokhtarian (2008), and have even been applied to look at various aspects of activity planning/scheduling as in Miranda-Moreno and Gosselin (2008) and Ruiz and Roorda (2008). The coefficients for the various probit models were all estimated using the QLIM procedure in the SAS statistical analysis program. The data used to estimate the planning order models is discussed in the next section.

9.4. Use of UTRACS Activity Planning Survey Data

The data used in the development of the planning order models was obtained from the UTRACS survey which is detailed in Part II of this thesis. Briefly, the UTRACS survey was conducted on 102 households from four counties in the Chicago region, Cook, Lake, DuPage and Will, with the sample split evenly between elderly and non-elderly households. Data collection was begun in April 2009 and ran through October 2009. Every individual completed an upfront interview collecting basic demographic data and routine activity patterns, and then carried a GPS data logger and completed the prompted recall survey for up to fourteen days. The dataset that was used in this study comprises more than 4100 activities and 3700 trips. The data was validated against reference data from the 2007 ACS and a recent household travel survey conducted in Chicago. A full description of the current data collection effort, including sample validation, bias estimation, recruitment, etc., can be found in Part II. Note that for modeling purposes the overall sample was filtered for non-routine out-of-home activities and split into "training" and "test" datasets for later validation purposes, with the 54 respondents who began the survey prior to August 4, 2009 placed into the training set. This left a total of 1858 activity observations in the training set and 240 in the test set used for planning behavior model estimation.

The distributions of the three dependent variable categories, i.e. attribute flexibilities, activity plan horizon, attribute plan horizons, obtained from the survey are shown in Table 1 below, with missing values omitted for the attribute plan horizons. The table shows the response distributions for each variable, while sample descriptive statistics for all independent variables are shown for the training data set. The frequency and duration variables are averaged over all observations of a specific activity type, such as "Primary Work", "Grocery Shop", etc. for each individual. These averages are then assigned to all observations of that type for each individual. The activity type indicators shown in the table and used in the model are aggregations of the 20 specific activity types into common categories, such as "Work", "Shop", "Discretionary", etc. as shown in the table. The distributions show that most of the observations are evenly split between inflexible and flexible attributes except for start time which tends to be much more flexible than the rest of the attributes. The activity and attribute plan horizon distributions display results which are realistic and compare favorably to observations from other plan horizon observations such as CHASE (Doherty et al 2004). The attribute plan horizon distributions show that the mode and location choices tend to be the most routine, with the start time and especially the duration decisions tending to be quite impulsive.

TABLE VI
PLANNING BEHAVIOR MODEL VARIABLE DESCRIPTIONS

Dependent Variable Distributions

	Inflex	**Flex**			
Mode Flexibility	52%	48%			
Personal Flexibility	42%	58%			
Location Flexibility	45%	55%			
Start Time Flexibility	17%	83%			
Duration Flexibility	43%	57%			
	Impulsive	**Same Day**	**Same Week**	**Preplan**	
Activity Plan Horizon	30%	32%	28%	10%	
	Impulsive	**Same Day**	**Same Week**	**Preplan**	**Routine**
Mode Plan Horizon	21%	25%	23%	9%	22%
Who-with Plan Horizon	31%	30%	25%	10%	5%
Location Plan Horizon	30%	26%	23%	10%	11%
Start Time Plan Horizon	43%	29%	16%	7%	4%
Duration Plan Horizon	70%	11%	8%	3%	8%

Independent Variable Descriptive Statistics

	Average	**Stdev**	**Min**	**Max**
Avg Duration (in days)[1]	0.06	0.10	0.00	1.12
Avg Frequency (per day)[1]	0.72	0.79	0.05	4.18
Student	0.09	0.28	0	1
Employed	0.82	0.38	0	1
Senior (65 yr old +)	0.54	0.50	0	1
Male	0.28	0.45	0	1
Teleworker	0.19	0.39	0	1
ICT User	0.72	0.45	0	1
ACT1 (work/school)[2]	0.11	0.31	0	1
ACT2 (personal)[2]	0.12	0.33	0	1
ACT3 (maintenance)[2]	0.10	0.30	0	1
ACT4 (discretionary)[2]	0.28	0.45	0	1
ACT5 (shopping)[2]	0.32	0.46	0	1
ACT6 (other)[2]	0.07	0.26	0	1

1 Calculated over all activities of specific activity type (20 types) for each person

2 Specific activity types are grouped into 6 general activity categories

9.5. Results for MVOP Attribute Flexibility Model

The first model estimated under the activity planning framework shown in Figure 3 is the Activity Attribute Flexibility model. This model determines the perceived flexibilities for the five primary activity attributes: mode, who with, location, start time and duration. As this is the first model estimated immediately after the activity is generated, it depends solely on the general activity type, the characteristics of the individual, and some simple history characteristics, such as the expected duration and the expected weekly frequency. As such, the activity flexibility attributes are limited to the data that is expected to be available at this point in the simulation. More accurate models of attribute flexibility can be generated (Lee-Gosselin et al 2006), where the flexibilities depend on other attributes of the activity, such as the duration, mode selected, etc., but these characteristics are not known at the point the flexibility model is utilized. This is due to the assumption of the flexibilities being fundamental, intrinsic aspects of a generated activity, rather than planned attributes, which in turn act as constraints on further planning. The results of this model estimation are shown in TABLE VII.

Overall, the model displays an acceptable fit to the multivariate flexibility responses. The results of the model estimation show that the use of a multivariate model in this case is warranted with significant, moderate correlations between the unobserved error terms of the who-with and start time latent variables and significant but minor correlations between the remaining attributes, with only the mode-location, person-location and duration-location correlations being insignificant. All coefficients of the model are significant at the 0.1 level and most are significant at the 0.05 level. The table shows the estimated coefficients for each response grouped into three categories. First there are direct and interaction effects of the individual characteristics. Second are the general characteristics of the activity. Finally, activity-type specific effects are show, where some of the individual and general activity characteristics are interacted with activity type indicators, with the "other" activity type as the reference category.

TABLE VII
ACTIVITY ATTRIBUTE FLEXIBILITY MULTIVARIATE PROBIT MODEL RESULTS

		Mode Flexiblity		Interpersonal Flexiblity		Location Flexiblity		Start Time Flexiblity		Duration Flexibility	
		β	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**	**β**	**t-stat**
	Constant	-0.384	-4.0	-0.338	-2.4	-0.369	-2.6	1.326	11.8	-1.239	-8.8
Individual	Employed	0 363	3 7	--	--	--	--	--	--	1 294	9.2
	Student	0 422	3 3	0.348	2 7	--	--	--	--	1 461	12.2
	Male	-0 218	-2 0	-0 537	-4 2	-1.174	-9.2	-0 387	-2.9	--	--
	Senior	-0.267	-3 3	0.260	2 8	-0 191	-1.7	-0 227	-2 5	-0.246	-2 8
	Male x Senior	0 692	4 5	0.478	2.9	1.347	7.1	0.485	2.9	-0.374	-3.7
	ICT user	--	--	0.532	5 2	-0.367	-3.3	-0 302	-3.2	--	--
	Teleworker	--	--	1.508	5.1	0.994	3.1	0.196	1.8	--	--
	ICT x Teleworker	--	--	-1.656	-5.6	-0.816	-2.5	--	--	-0.235	-2.4
Act	Avg. Frequency	0 231	4.1	--	--	--	--	--	--	--	--
	Avg. Duration-	-	--	--	--	--	--	--	--	1.300	2.2
Activity Type	ACT1 (Work/School)	--	--	-1 391	-7.3	--	--	--	--	0.621	1.8
	x *ICT user*	0.569	3.3	--	--	--	--	--	--	0.995	2.9
	x *Teleworker*	--	--	1 352	5.5	1 024	2 5	--	--	-1 124	-3.5
	x *Avg Frequency*	-1.039	-5.9	--	--	2 325	6.9	--	--	-0.562	-3.5
	x *Avg Duration*	--	--	--	--	--	--	--	--	-2 071	-2.7
	ACT2 (Personal)	--	--	-0 598	-3 6	--	--	--	--	--	--
	x *Avg Duration*	--	--	11 034	4 3	-8.967	-4.0	3.376	1 7	--	--
	ACT3 (HH Needs)	--	--	-0.618	-3.0	--	--	-0.401	-1.7	--	--
	x *Avg Frequency*	--	--	1.728	3.0	-1.022	-1.9	1.301	1.7	--	--
	ACT4 (Discretionary)	--	--	--	--	0.904	5.7	--	--	--	--
	x *Avg Frequency*	--	--	0.438	2.2	0.637	2.8	--	--	0.770	4.8
	x *Avg Duration*	--	--	6.708	6 1	-8 326	-7.3	--	--	--	--
	ACT5 (Shopping)	--	--	-0.607	-4 8	2.383	17.7	-0.602	-5.6	--	--
	x *Avg Frequency*	--	--	0.326	4.3	--	--	0.193	2.5	0.488	7.5

Correlation Coefficients

	ρ	t-stat	ρ	t-stat	ρ	t-stat	ρ	t-stat	ρ	t-stat
Mode	1	--								
Person	0.10	2.4	1	--						
Location	***-0.05***	***-1.1***	***-0.03***	***-0.6***	1	--				
Time	0.10	2 1	0.31	7.3	-0.11	-2.1	1	--		
Duration	0.12	3.0	0.17	3.9	***0.03***	***0.5***	-0.10	-2.1	1	--

Likelihood ratio:	0.180

The signs and magnitudes for the model mostly conform to expectations of variable impacts on the underlying latent variable. As an example, consider the mode flexibility model as shown. The coefficients show that in general individuals who are employed or are students have increased flexibility in mode choice, possibly due to the higher priority activities these individuals are presumably engaging in. In other words they may have first choice of transport within their respective households. Males and seniors are generally less flexible (although male-seniors are in fact more flexible as compared to the base case of non-senior-females) as is often seen in mode choice studies. The frequency with which the activity is performed also impacts the mode flexibility, with flexibility generally increasing with increasing frequency, although this is not the case for work activities where the flexibility is greatly decreased with frequency. This shows the difference between mode choice for traveling to the frequent work activity, where the choice may be locked in to a routine pattern, versus the mode flexibility for frequent non-work activities. The final parameter in the mode choice flexibility model is if the individual is an information and communication technologies (ICT) user. For frequent ICT users the mode choice decision for work activities is more flexible, perhaps reflecting the greater opportunities for coordination and planning for different mode types, such as carpooling, transit, etc. which are enabled by these technologies.

Similar analyses can be performed for the remaining four flexibility responses; however several interesting results can be highlighted. One focus of the survey was on the use of teleworking and ICT by the survey respondents and the impacts these may have on the planning process. In general, being an ICT user increases the flexibility for the mode, who-with and durations of activities, where this is limited to work activities only for the mode and who-with decisions, and it decreases the flexibility of the location and start time decisions. The impact of ICT use on mode flexibility for work activities was discussed above, while the use of ICT may increase the duration flexibility of work activities through a type of substitution effect whereby employees who are not truly teleworkers may still be able to finish work at home or elsewhere through the use of ICT resulting in more flexible work durations. Note that this is effect is not seen for true teleworkers who actually show less duration flexibility than traditional workers, further supporting this partial substitution possibility. In contrast, and somewhat unexpectedly, the individuals who use ICT show less flexibility in location and start time. Since the responses represented here are "perceived" rather than "actual" flexibilities, it is possible that the use of

Overall the model fits well and should be able to give acceptable estimates of attribute flexibility for later use in activity planning simulation The model includes several important policy variables of interest, including ICT use and Teleworking, and several state variables, the average frequency and duration of the activity type, which can be updated during simulation to represent dynamic effects In addition to serving as important inputs to the subsequent plan order models as shown in Figure 11, the flexibilities can also serve as constraints on later attribute planning models For example, for a location decision perceived as inflexible a limited choice set can be developed, possibly from a list of acceptable past locations, while in contrast a flexible location choice could have a more extensive choice set

9.6. Results for Activity Plan Horizon Model

The results of the overall activity plan horizon ordered probit model are shown in TABLE VIII The model specifies the activity plan horizon in one of four levels, the activity can be impulsive, planned the same day, planned the same week, or preplanned Note again that this modeling framework specifically excludes "routine" activities, which are modeled separately and in a different fashion within the simulation All coefficients shown significant at the 0 05 level, except for several of the activity type interact terms (Act3 x inflexible duration, Act4 x ICT user, Act4 x average duration) which were retained for conceptual reasons The model is similar to others that have been developed from different activity planning data sources, for example Mohammadian and Doherty (2006), except that again the model does not depend on any specific characteristics of the activity Only general characteristics of the activity type (type, average duration, average frequency) and the flexibilities of the specific instance of the activity, in addition to the individual characteristics are utilized in the model, as specified by the framework in Figure 11

TABLE VIII
ACTIVITY PLANNING HORIZON ORDERED PROBIT MODEL

	Variable	**β**	**t-stat**
	Constant	0 130495	0.62
Person	Employed	0.767701	4.23
	Frequent ICT usage	0 485362	2.4
	Teleworker	-0.560652	-4.38
Activity	Inflexible Location	0 640303	4.93
	Inflexible Start Time	-0 63621	-5.47
	Inflexible Duration	-1.498554	-5 34
Activity Type	ACT1 (Work/School)	1 049907	2.47
	x *Employed*	-0.892963	-2.09
	x *Student*	1.717603	2.25
	x *Inflexible Location*	-0 789474	-1.88
	x *Inflexible Duration*	2 241387	5 03
	x *Average Frequency*	-0.446779	-2.48
	ACT2 (Personal)		
	x *ICT User*	-0.613958	-2.09
	x *Inflexible Duration*	1 497258	4.11
	x *Average Duration*	15 248565	4.73
	ACT3 (Maintenance)		
	x *Employed*	-0 745918	-2 52
	x *Student*	-1.115487	-2.21
	x *Senior*	1.049812	3.42
	x *Male*	-0.593425	-1 92
	x *Inflexible Duration*	0.633234	1.69
	x *Average Frequency*	1 573672	2.59
	ACT4 (Discretionary)		
	x *Student*	0 837724	2.74
	x *Senior*	0.681377	3.63
	x *Male*	-0.793118	-3.99
	x *ICT User*	-0.432584	-1.71
	x *Inflexible Duration*	1.404	4.22
	x *Average Frequency*	0 519961	2.59
	x *Average Duration*	2.200	1.81
	ACT5 (Shopping)		
	x *Employed*	-0.610606	-2.55
	x *Senior*	0.415577	2.22
	x *ICT User*	-0.752066	-2.89
	x *Inflexible Duration*	1.128966	3.55
	x *Average Frequency*	0.289143	3.49
Limits	α_2	1 65	27 23
	α_3	3.51	36.52

Likelihood ratio·	0.095

The model coefficient estimates had effects as expected. Employed individuals tended to have a greater degree of preplanning for "personal" and "discretionary" activities as would be expected. These types of activities tend to require a greater planning/scheduling effort as they more difficult to fit around a work schedule and usually tend to involve others. Users of ICT tended to exhibit more preplanning in "work", "maintenance" and "other" activities and less preplanning in "personal" and "shopping" activities, possibly due to the greater ease with which personal and shopping activities can be planned through the use of ICT. Teleworkers exhibited less preplanning for all activity types, probably due to greater scheduling freedom from working at home. The average frequency and duration of the activity type also impacted the plan horizon, with longer, more frequent activities generally being more preplanned, since the longer an activity is and the more the activity is conducted, the more scheduling effort seems to be required.

Finally, the flexibilities of the various activity attributes also impacted the overall activity plan horizon. For example, an activity with an inflexible location decision tended toward being more preplanned, except for the "work" activities. In contrast, inflexible start times and durations tended to either have no impact or to make the activity less preplanned, except for inflexible duration "work" activities which tended to be more preplanned. The location results are intuitive as travel to a specific location is probably more difficult to plan and therefore more preplanned (impulsive activities tend to have more flexible locations as they are usually planned opportunistically). Meanwhile, the inflexible start time results may reflect that generally preplanned start times are viewed as changeable. Work activities with inflexible durations are more preplanned as would be expected when scheduling a large portion of the day for an inflexible amount of time, while maintenance activities with inflexible durations are less preplanned as maintenance activities tend to be short activities ("pick-up/drop-off", etc.), where the inflexible duration probably represents more of a minimum time in which the activity can be completed, rather than a true scheduling inflexibility.

9.7. Activity Attribute Plan Horizon Modeling Results

The final model within the "Activity Planning Order" model framework is the individual attribute planning order model. This model uses the previous two models as input, along with the individual and activity type attributes, to estimate general plan times for each of five activity attributes (mode, who-with, location, start time, duration), within the overall simulation. The determination of each correlated attribute plan time through the use of the multivariate ordered probit model creates the overall order in which the attributes are planned. The results for each response can be either "impulsive", "same day", "same week" or "preplanned". These then give a general time frame within the overall simulation at which each decision is made. The actual coefficient estimates, threshold values, and correlation parameters for each response, as well as the overall model fit are shown in TABLE IX. The model shows reasonable fit and the correlation coefficient results also show some interesting results. The mode plan horizon and who-with plan horizon are weakly positively correlated with the planning of all of the other attributes. The location plan horizon has a small to moderate positive correlation with the start time and duration plan horizon response. And finally, the start time and duration have a strong correlation as expected. All correlation parameters are significant at the 0.01 level, except the "who with-to-location" correlation parameter which is significant at the 0.05 level.

The table shows all of the parameter estimates for the five attribute plan horizon responses. The coefficients are almost all significant at the 0.10 level with most significant at the 0.05 level. Some marginally significant parameter estimates where retained for their policy relevance, such as the average duration of the work activity under the mode planning response. Overall, the model displays effects for each response that where generally in line with expectations. All attribute plan horizons are greatly impacted by the overall activity plan horizon with more impulsive activities logically having more impulsive attribute plan horizons, to a greater or lesser degree, for each response. The impacts of the other variables are discussed below for each individual attribute response.

TABLE IX
ACTIVITY ATTRIBUTE PLANNING HORIZON MVOP MODEL

		MODE		WHO-WITH		LOCATION		START		DURATION	
	Variable	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
	Constant	0 618	3 09	4.096	22 37	2 079	8.96	1.612	9.24	-1.268	-6.85
Individual	Employed	0.634	5.83	--	--	0 203	1.95	0 359	3.52	0.745	5.31
	Student	1.044	9.24	--	--	0 351	3.25	--	--	--	--
	Senior	-0.115	-1.61	--	--	--	--	--	--	0.159	1.82
	Male	--	--	--	--	--	--	--	--	0.126	1.56
	Frequent ICT usage	0.130	1.60	--	--	0.840	8.36	-0.146	-1.58	--	--
Activity	Actplan - Impulsive	-1 527	-8 64	-5 533	-28 62	-3 209	-17.67	-3 178	-20 47	-1 462	-9.70
	Actplan - Same day	-0 492	-3 36	-2 912	-16 85	-1 401	-7 48	-1 570	-10.21	-0 518	-3.74
	Actplan - Same week	-0 272	-1 74	-1 231	-7.13	-0 582	-3.03	-0.933	-6.50	-0.357	-2.54
	Inflexible Start Time	--	--	--	--	--	--	--	--	0.295	2.59
	Inflexible Duration	0.106	1.55	--	--	--	--	0 163	2.32	0.839	8.89
	Avg Duration (in days)	--	--	--	--	1.846	9.36	--	--	--	--
	Avg Daily Frequency	--	--	--	--	--	--	--	--	0.266	3.67
Activity Type	Act1 (Work/School)	--	--	--	--	--	--	--	--	--	--
	x *Teleworker*	0 456	1.75	--	--	--	--	0.756	2.86	0.877	2.57
	x *Inflexible Location*	--	--	--	--	0.951	5.85	--	--	--	--
	x *Avg Duration*	0.786	1.52	--	--	--	--	--	--	--	--
	Act2 (Personal)	0.262	2.12	--	--	--	--	--	--	0.321	2.26
	x *Student*	--	--	0 825	3.86	--	--	--	--	--	--
	x *ICT User*	--	--	--	--	-0.736	-5.25	--	--	--	--
	x *Inflexible Duration*	--	--	--	--	--	--	--	--	-0.397	-2.01
	Act3 (Maintenance)	--	--	--	--	--	--	--	--	--	--
	x *ICT User*	--	--	--	--	-0 693	-4.77	--	--	--	--
	x *Inflexible Start*	--	--	--	--	--	--	0.616	3.53	--	--
	x *Actplan - Sameweek*	0.354	1 59	--	--	--	--	--	--	--	--
	Act4 (Discretionary)	0.377	3 13	--	--	--	--	--	--	--	--
	x *ICT User*	--	--	0.359	2.95	-1.034	-6.36	0.186	2.01	--	--
	x *Inflexible Location*	--	--	--	--	0.279	1 77	--	--	--	--
	x *Avg Duration*	-3.922	-3.88	-5.691	-6.93	--	--	--	--	--	--
	Act5 (Shopping)	0.196	2.19	--	--	--	--	0.206	1.57	--	--
	x *ICT User*	--	--	--	--	-1.166	-10.43	-0.498	-3.09	--	--
	x *Inflexible Duration*	--	--	--	--	--	--	--	--	-0.277	-2.25
	x *Inflexible Start*	--	--	--	--	--	--	--	--	-0 334	-1.98
Limits	α_2	0.835	17.43	2.029	17.55	1.305	16.73	1.151	17.24	0.435	10.32
	α_3	1.486	26.87	3.614	30 29	2 316	27.63	2.027	21.91	0.879	-2.01
	α_4	1.794	30.76	4.402	44.22	2.796	34.88	2.643	33.04	1 096	2.58

Correlation Coefficients

	ρ	t-stat	ρ	t-stat	ρ	t-stat	ρ	t-stat	ρ	t-stat
Mode	1	--								
Who-with	0 143	3 8	1	--						
Location	0 148	4 2	0 104	2.2	1	--				
Start time	0 159	4 1	0 181	3.4	0 352	11.4	1	--		
Duration	0.187	4.5	0 178	3.2	0.218	5.7	0.539	19.2	1	--

Likelihood ratio:	0.152

The mode choice plan horizon is shifted toward preplanning for individuals who are employed and/or who are students, and to a lesser extent by ICT usage, while there is a slight shift toward impulsive mode planning for seniors. These parameter estimates all fall in line with expectations as employees/students tend to have more preplanned/routine mode choice due to the mandatory work/school activities, while seniors do not. As far as activity-type specific effects, individuals who are teleworkers and activities with long durations tend to have more preplanned mode choices for "work" activities. Mode choices also tend to be more preplanned in general for "personal", "discretionary" and "shopping" activities, although this is most likely due to many of these type of activities occurring during routine or preplanned tours in the case of "shopping" and "personal" activities, while discretionary trips (socializing, eating out, entertainment, etc.) tend be conducted more as stand-alone tours and often involve others, leading to more preplanning. One unusual result is that long average duration discretionary trips tend to be more impulsive in the mode choice. This counteracts the discretionary activity constant such that discretionary activities less than approximately two hours long have a net increase in mode preplanning while longer activities have a decrease in preplanning.

The interpersonal plan horizon is determined almost entirely by the overall activity plan horizon. However, students tend to preplan the party composition more for "personal" activities, while discretionary activities show a small increase in preplanning for ICT users and a large decrease in preplanning for long average duration activities similar to the mode choice. The results for the discretionary activities are interesting, because as the results in Table 3 show, longer duration discretionary activities have an increased propensity toward preplanning for the overall activity while the results for the mode and who-with plan horizons show increased impulsiveness with increased average duration, showing that activities of this type are planned first while the details of who is involved and the mode chosen are filled in later.

The location plan horizon is influenced by several important attributes of the individual and the specific activity type. Similar to the mode plan horizon, employed individuals and students have more preplanned location choices in general, due to the more mandatory nature of their activity patterns. ICT users have more preplanned location choices for work/school activities, but more impulsive discretionary and shopping location choices, possibly due to the greater planning possibilities available through the use of communications technology.

Especially for discretionary types of activities, ICT lets users more quickly and easily find suitable locations through internet searches, location-based services available on cell phones, etc, which probably reduces the need for preplanning. The average duration of the activity also is a factor in the location planning, with longer activities which possibly have higher priorities having a higher degree of preplanning. Finally, as would be expected, for work and discretionary activities with an inflexible location, the location choice is more preplanned.

The start time planning horizon also shows some interesting results. Much like with the other attributes, employed individuals and students exhibit a higher degree of preplanning for all activity start times, again due to the more mandatory nature of their schedules. One interesting result is that frequent ICT users show slightly more impulsive start time planning for all activities except for discretionary activities (which are often conducted with others and therefore prescheduled) and much more impulsive planning for shopping activities, as expected due to the greater information gathering and scheduling coordination possibilities provided by ICT. For one example of this, looking up operating hours for a store can allow for more impulsive start time planning as the user can save time by predetermining that the store will still be open rather than wasting time driving to a store to find that it is closed. For teleworkers the start time tends to be more preplanned for work activities to an even greater degree than other employed individuals, which shows that even teleworkers tend to organize their at-home working schedules around routine blocks of time. Finally, the flexibility of the activity durations and the start times for maintenance activities also impacts the start time planning, with less flexibility in these measures leading to greater preplanning as expected.

Finally, the duration plan horizon results are similar to those for the start time, with similar impacts from the employed, student and teleworkers indicators. Additionally, the flexibility measures of the start time and duration choices have a similar impact as seen in the start time planning, with less flexibility leading to more preplanning (although the impact is smaller on personal and shopping activities). The duration tends to be more preplanned for more frequent activities, probably due to the more frequent activities being part of a routine pattern. Finally, a greater degree of preplanning of the duration is seen for both seniors and males, although the effect is fairly small.

9.8. Model Validation and Accuracy Estimation

After the various models of the activity planning order framework were estimated, an assessment of the accuracy and validity of the model was needed This was evaluated in a number of ways First, the accuracy of the overall simulation for each response from the input or "training" sample was evaluated against the expected "null model" response accuracies, which were obtained from applying the observed response distributions This enables a determination of the effectiveness of the model system in predicting responses Next, the same procedure was applied to a second data set, the "test" data set, obtained through the same UTRACS survey to test for potential over-fitting in the model system For both the training and test sets, in addition to the response accuracies, two additional accuracy measures were calculated These measures evaluate how well the overall order of the activity attribute planning is estimated Finally, the model was partially validated against other activity planning data sources where available

The first validation exercises performed were the comparisons between the simulated responses from the training and test datasets to the expected null model responses, with each data set as defined in Section 9 4 The results for this analysis are shown in TABLE X The accuracies show the average percentage for each response in the three components of the planning order framework which were estimated as observed in each dataset, averaged over 1000 simulation runs So, for example, the table shows that 53% and 54% of mode flexibility measures were estimated correctly on average for the training and test datasets respectively It should be noted here that the accuracies shown for the activity plan horizon and activity attribute plan horizon include the effects of the lag variables from the prior models In other words, the errors from the previous model are propagated and accounted for in this analysis, i e the simulated flexibility values are used in the plan horizon models, etc

The planning order accuracies represent an important validation, as the overall intent of the model framework is to specify the planning order The accuracy of the planning order was calculated in two ways, for the exact and the approximate planning order The exact order accuracy is the percentage of observations for which the attributes are simulated in the exact order in which they are observed The order is determined based on the planning horizons, i e "routine" comes before "preplanned" comes before "same week", etc with the attributes then sorted into first, second, third, etc planned attributes Simulating all five attributes in the exact observed order, where each attribute can have five response values, is fairly difficult however, so another "approximate" plan order accuracy was also utilized. The approximate accuracy is defined as the number of simulated observations which have no attribute out of place by more than one spot from the observed orders, i.e. if the mode is planned first in the observed activity order, it can be planned no more than second for the order to still be approximately correct.

TABLE X
MODEL ACCURACY COMPARED TO NULL MODEL

	Simulated Accuracy[1]		Null Model Accuracy[2]		% Improvement Over Null	
	Train	Test	Train	Test	Train	Test
Mode Flexibility	53%	54%	50%	50%	5%	7%
Personal Flexibility	59%	54%	51%	50%	16%	9%
Location Flexibility	74%	73%	51%	50%	47%	46%
Start time Flexibility	69%	69%	68%	67%	1%	3%
Duration Flexibility	60%	58%	50%	50%	20%	15%
Activity Plan Horizon	32%	32%	28%	28%	16%	13%
Mode Plan Horizon	24%	22%	17%	17%	42%	30%
Who-With Plan Horizon	33%	34%	26%	26%	27%	30%
Location Plan Horizon	30%	31%	22%	23%	37%	34%
Start Time Plan Horizon	37%	34%	30%	28%	21%	19%
Duration Plan Horizon	55%	48%	51%	44%	9%	7%
Order Exact[3]	4%	3%	1%	1%	261%	177%
Order Approximate[4]	53%	50%	34%	34%	54%	45%

Note All differences between simulated average and null model accuracies are significant at the 0 01 level

1 Averaged over 1000 simulation runs

2 Null model estimated by applying response distributions from training dataset randomly to each dataset

3 Accuracy of predicting the exact order in which attributes are planned

4 Accuracy of predicting the approximate order in which attributes are planned (no attribute out of order by more than one place)

The response and order accuracies have been compared to null model expectations for both the training and test datasets, calculated from the observed response observations. The results in TABLE X show that the model gives marginal to moderate improvements in the accuracies (from a low of 5% for the mode and start time flexibilities to a high of 48% for the location flexibility) showing that the model gives some performance benefit. In addition, similar improvements over the null model are also seen in the test dataset, showing that over-fitting is not likely to be an issue. In addition to the improvement in the individual response accuracies, both the training and test set simulations showed an improved ability to correctly estimate the proper planning orders as compared to the average of a null model simulation (no closed form expected values can be determined for null model order accuracy so it was determined through Monte Carlo simulation). So, overall, the modeling framework for estimating the activity attribute planning order shows good improvement over the null models, showing that the framework is useful.

A second validation exercise was performed to determine how well the estimated models can replicate activity flexibility and planning horizon responses from other surveys, from different spatial and temporal contexts. No single data source available includes all of the flexibility and plan horizon responses estimated by the model, but several different data sources do contain observations on several of the responses separately. These include the CHASE dataset (Doherty et al 2004), which includes observations on four of the five flexibility measures as well as the overall activity plan horizon measure, and the OPFAST dataset (Lee-Gosselin 2005). The OPFAST dataset includes measures of spatial and temporal flexibility that approximate a combination of both the flexibility and attribute plan horizons as defined in the current work. The flexibilities in the OPFAST dataset are given in terms of whether each decision is habitual/routine (Fixed), Planned, or Impulsive, so an aggregation of the responses into habitual vs. non habitual will yield approximately the same measure as the location and start time flexibilities, although this does not allow for the possibility of habitual planning with flexible responses and vice versa which are recorded in the UTRACS data. Meanwhile the unaggregated OPFAST responses correspond to an aggregated version of the attribute planning horizons collected in UTRACS (with same-day, same-week and preplanned responses in UTRACS corresponding to the "Planned" category in OPFAST). The OPFAST data further refines the timing plan horizon by defining various plan horizons within the "Planned" category that correspond to those used in this work. The same accuracy comparisons as performed for the training/test datasets were performed for the CHASE and OPFAST data for all available responses.

The results in TABLE XI show the results of these various validation exercises. The accuracies and improvement over the null models are shown for all available responses found in each dataset. These include four of the five flexibility measures (excluding mode flexibility) and the activity plan horizon found in CHASE, and the location and start time flexibility and plan horizons found in OPFAST. The input data sets for each test were derived from each data source using similar methods as for the UTRACS data, with conversions being made as necessary so all dependent and independent variables conform. This primarily means that all at-home activities and all routine activities were excluded from each dataset, while input variables such as the ICT usage where imputed from existing variables in each case and activity types where transformed to match those used in UTRACS. All of the null model accuracies were calculated using the response distributions from each data set.

TABLE XI
VALIDATION WITH CHASE AND OPFAST DATA

	Simulated Accuracy[1]		Null Model Accuracy[2]		% Improvement Over Null	
	CHASE	OPFAST	CHASE	OPFAST	CHASE	OPFAST
Personal Flexibility	63%	--	55%	--	15%	--
Location Flexibility	53%	47%	50%	53%	6%	-11%
Start time Flexibility	52%	74%	51%	88%	2%	-15%
Duration Flexibility	52%	--	51%	--	1%	--
Activity Plan Horizon	29%	--	26%	--	13%	--
Location Plan Horizon	--	38%	--	36%	--	6%
Start Time Plan Horizon	--	30%	--	26%	--	17%

Note All differences between simulated average and null model accuracies are significant at the 0 01 level
1 Averaged over 1000 simulation runs
2 Null model estimated using observed response distributions from each dataset

The results show that the model outperformed the null model assumptions for both the flexibilities and the plan horizon for the CHASE test. Although the performance is only moderately greater in some cases, such as the start time and duration flexibilities, it is important to remember that these comparisons are against the null model as calculated using the actual CHASE data. Therefore, these improvements show that the model is transferable to some degree to other contexts, i.e. it is not overfit to the UTRACS dataset or Chicago region. Similar results are shown for the OPFAST test, although in this case the location and flexibility accuracies are outperformed to some degree by the null model. However, the location and start time attribute plan horizons do show significant and more than marginal improvement over the null model. The poor results of the flexibility response are likely due to the different definitions of flexibility used in the OPFAST as previously discussed, while CHASE and UTRACS share similar measures for these responses. The plan horizons, however, are defined similarly in all of the surveys and the improvement shown over the null model for this test is encouraging. Overall, the model framework shows potential for having good transferability properties although clearly more test, preferably with data containing all of the modeled responses, are needed to further evaluate this possibility.

9.9. Discussion and Conclusions

This chapter has discussed the ADAPTS planning framework that was developed to simulate planning, scheduling and execution of activity patterns in an integrated, dynamic framework. The development of the series of models which comprise the activity planning order framework was discussed. This system of models forms the core of the ADAPTS planning framework which allows the simulation of activity planning in a non-sequential fashion, where the individual attribute choice decisions, i.e. destination choice, start time, party composition, mode and duration, can be made at any time before the activity is executed and in any order. This helps relaxing some of the assumptions regarding activity planning and allows the simulation to more closely approximate the actual underlying process of activity scheduling.

The activity planning order framework was developed using data collected from a GPS-based prompted recall activity and travel survey, the UTRACS survey. This survey collected data on activity-travel patterns, attribute plan horizons and spatial, temporal and interpersonal fixities over a period of two weeks. The survey shows similar results on some of the fundamental activity planning measures (activity plan horizon, attribute horizons, flexibilities) to observations seen in other survey.

The activity planning measures from the survey, along with other socio-demographic and activity related variables, were used as input to a series of probit models (multivariate, ordered and multivariate ordered probit) which model the flexibilities, activity plan horizon, and attribute plan horizons, in that order, where the results from the previous model are used as lag variables in the subsequent models. Two of the models, the flexibility and plan horizon models, were multivariate in nature with responses for each primary attribute of an activity modeled simultaneously. This enabled an estimate of the correlations between the random errors for each model, in addition to the other model parameters. The models all show moderate goodness-of-fit with parameter estimates which were reasonable and conformed to prior expectations about their impacts on each dependent variable (or variables for the multivariate models). More importantly after a full simulation is run using the input data, the model responses all show an improvement in accuracy over expected null model accuracies for both the data used to develop the model and a test data set. This shows that the full planning order model system is working, not propagating an excessive amount of simulation error between models, and is not overfit to the training data. In addition, similar results are even observed when using other datasets, namely the CHASE and OPFAST data from Toronto and Quebec City respectively, showing that the model is fairly transferable, which is a significant finding. Although the goodness-of-fit measures and improvement over null model accuracies are marginal for some responses, the model does provide a transferable framework that outperforms null model expectations and relates the flexibility and planning horizons to important planning and policy variables, i.e. average frequency and duration, employment/student states, teleworking, ICT usage, to show how changes in any of these variables can impact the underlying activity planning process.

10. ACTIVITY ATTRIBUTE PLANNING MODELS

10.1. Introduction to Attribute Planning – Destination Choice

As has been repeatedly documented in this work, it has been recognized that significant issues exist in all activity-based microsimulation systems and that there are areas where theoretical and practical developments still need to be made (Litwin and Miller, 2005), including in modeling the underlying decision processes behind activity scheduling and representing the interdependence between the various decisions underlying the activity scheduling process (Miller 2005), which again is the core focus of this work. The ADAPTS model attempts to simulate the dynamics of activity planning behavior through the concept of planning horizons, which specify when the various decisions about each activity are made. This means, however, that for each attribute planning decision, such as mode choice, party composition, and destination choice, the dynamics of planning must be explicitly incorporated, i.e. how does the destination choice for an impulsive activity differ from the choice for an activity planned two weeks ago? This is the topic this chapter seeks to address. In the current case only the destination choice model has been fully implemented with regard to incorporating planning dynamics. However, the development of the destination choice model documented in this chapter provides a template for developing all of the other needed dynamic attribute planning models.

Many examples of disaggregate destination choice models exist in the literature. Early examples include Burnett (1974) and Ansah (1977) among many others. Destination choice formulations have been extended to more closely represent choice behavior with the development of the competing destinations model (Fotheringham, 1983) and later extensions (Bernardin et al. 2009; Schussler and Axhausen, 2009) which attempt to account for systematic similarities and differences between destinations in various ways. Discrete choice models of destination choice have further been extended to include more advanced formulations including correlated errors in a workplace location choice model for physicians (Bolduc et al 1996), and the development of a mixed generalized extreme value model for residential location choice (Sener et al. 2009), which take into account the unobserved correlations between destinations. Others have looked at the constraints imposed by the daily activity patterns of individuals on destination choice. Arentze and Timmermans (2007) incorporated the concept of detour time derived from the daily activity pattern into the destination choice model to account for trip chaining effects. The constraints on activity patterns are also addressed from the perspective of time geography; in Miller (2004) for example. Finally, another important consideration in discrete choice modeling is handling choice set formation, i.e. the zones for each individual from which each discrete choice is made, which is not a straightforward topic when moving to more advanced models. Thill and Horowitz (1997) attempted to account for scheduling constraints and choice set formation by modeling the choice set formation process within the destination choice model, as did Zheng and Guo (2008) through their spatial two-stage model. Reviews of research in choice set formation can be found in Thill (1992) and Pagliara and Timmermans (2009).

The ADAPTS destination choice model builds on past work in destination choice modeling to develop a new set of destination choice models for the Chicago region using the recent Travel Tracker Survey data (CMAP 2007), under a variation of the competing destinations framework. The key concept of the model is the assignment of an available set of destination choices for each choice situation which represents all of the destinations that could theoretically be considered by an individual given their space-time and planning constraints, dependent on what has previously been planned so that planning dynamics are explicitly incorporated into the model. This chapter is organized as follows. First, a discussion of the modeling framework is provided. Next a discussion of the data utilized in the estimation of the model and the model application context is discussed. Results of the model estimation are then provided. A validation of the model results is then performed and discussions and conclusions are presented.

10.2. Model Formulation

The destination choice model discussed in this work has been developed as a discrete choice model using the multinomial logit (MNL) framework, with several modifications to account for the influence of surrounding zones, and the addition of a new space-time prism constraint on the choice set formation. The basic multinomial logit model is well documented in the literature (Ben-Akiva and Lerman, 1985) and is derived from random utility maximization theory, which states that for each decision maker n, and zone i, there is a utility U_{in} associated with selecting zone i which is composed of both a component observable to the modeler V_{in} (systematic utility) composed of a linear combination of observed data x_{in} and parameters β, to be estimated and an unobservable random error component ε_{in} where the error components are independent and identically distributed (IID) with a Type I extreme value (Gumbel) distribution for each zone. Under these assumptions the probability of selecting any zone i from a choice set of zones C can then be given by the formula:

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j \in C} e^{V_{jn}}} = \frac{e^{\sum \beta_i x_{in}}}{\sum_{j \in C} e^{\sum \beta_j x_{jn}}} \tag{16}$$

This model forms the basis for the destination choice models for the various activity types. A discussion of the planning constrained choice set formation procedure and MNL model formulation with competition and agglomeration effects follows.

10.2.1 Choice Set Formation

Before developing the model specification for the planning constrained destination choice model, it is necessary to address the role that choice set formation plays. Choice set formation has long been recognized as a challenging aspect of destination choice modeling (Thill, 1992) for a variety of reasons, chief among them the large number of alternatives in the *Universal Choice Set*, consisting of all potential activity locations in the modeled region. Many choice set formation methods have been previously proposed in the literature (Thill, 1992; Pagliara and Timmermans, 2009). The method proposed in this work is based on previous work in using space-time constraint on choice set formation within activity-based models (Arentze and Timmermans, 2000; Kitamura et al. 1997), using the concept of the time-space prism (Hagerstrand, 1970). The current model is operationalized with the UTRACS data set documented in Part II of this work, which allows the development of a *Planning Constrained* choice set formation procedure. The formation of the choice set and subsequent activity destination selection are then used to make destination choice decisions for agents in the ADAPTS framework.

This procedure differs from previous instances of developing model using space time constraints, as the constraint on the travel time are based not on the travel times to the preceding and following activities surrounding the current activity (or on the preceding and following fixed activities as in PCATS (Kitamura et al. 1997), but rather on the constraints set by the preceding and following activities *which were planned before the current activity*, called the *prior planned activities*. The prior planned activities for any activity observation are simulated using the *Activity Planning Horizon* model presented in Chapter 9, which specifies how long an activity was planned before it was observed The previously developed activity planning horizon model is an ordered probit model with four levels of planning horizon (impulsive, same day, same week, preplan) which uses individual, activity-type and schedule-level data as input Details of the activity planning horizon model (Auld and Mohammadian, 2009) were documented in Chapter 9 of this work The procedure for specifying the choice set is then to specify when each non-fixed activity (i e not primary work, school, etc) was planned through simulation using this plan horizon model Then travel time constraints to each activity are set based on the simulated planning times of the surrounding activities

This is illustrated in the diagram in Figure 12, which shows two example location choice situations in a 1-dimensional space In each case the individual has a daily activity pattern of Home-Social-Shop-Work observed from travel survey data The *Activity Planning Horizon* model, shown in Table 1, would then be applied to each activity in this pattern to determine the order in which the activities are planned, based on household, individual and activity-level characteristics So, the two choice situations shown in Figure 12 (a) and (b) differ only in the order in which the activities are planned Note that in the example, only the location decision for the *Shop* activity will be discussed In the first part of the figure, there is a preplanned shopping trip on the way to the fixed work activity, while the *Social* activity is estimated as *impulsive*, so it does not factor into this location choice The space-time constraints in this case are set based on the time leaving home and the time arriving at work and the feasible travel speed In contrast, Figure 12 (b) shows a similar situation, but with the social visit being preplanned and the shop activity estimated to be impulsive In this case the location choice would be estimated first and would therefore constrain the available choices for the shopping activity The end time and location of the social visit severely limit the destination options for the impulsive shopping activity as seen in the figure

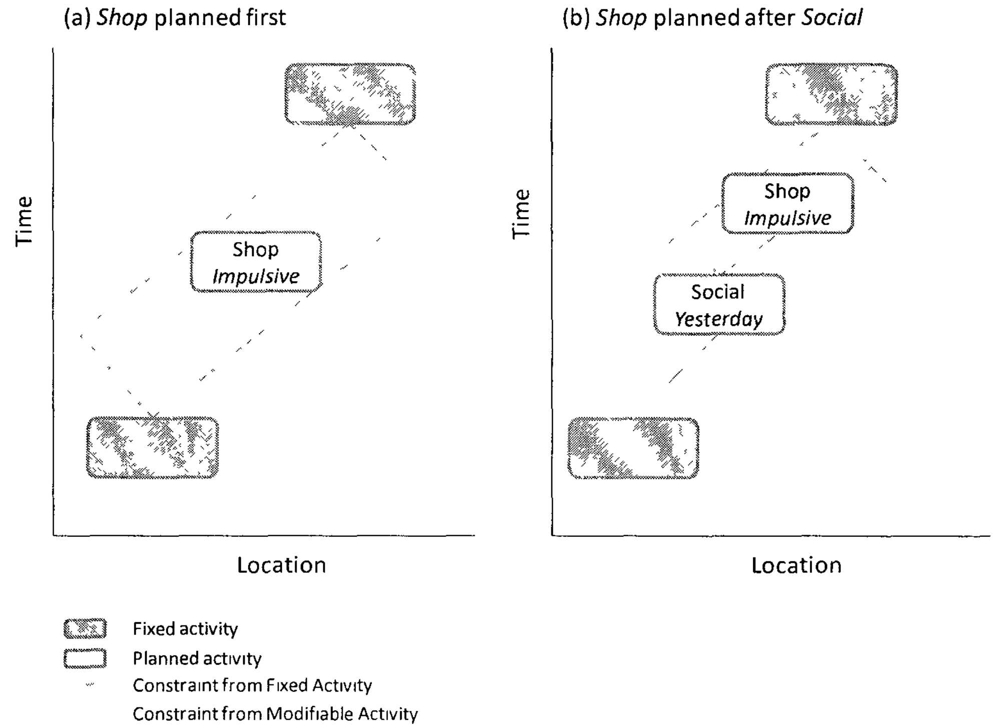


Figure 12. Example of Planning Constraints on Choice Set Formation

The process described above is followed for all activities to develop what is called the *Available Set*. This set A is defined as the feasible choices from the universal set that can be reached given the space-time planning constraints imposed by the other activities in the schedule. The definition of the available set is then necessarily accomplished through simulation by applying the planning horizon model discussed in Chapter 9 to all choice observations to estimate the ordering in which the activities were planned as described above. The model is an ordered probit model with four plan horizon levels, including "impulsive", "same day", "same week", and "preplanned". The model parameters are shown in TABLE VIII.

This process, however, only defines the available set, which can still have quite a large number of alternatives depending on the constraints. Since it is unlikely that all alternatives would be considered in actuality, a *Choice Set* is derived from the alternative set through *Stratified Importance Sampling* (Li et al, 2005), where a small stratified choice set is selected with N_c elements. In this work the available choices are stratified according to the

Deflected Travel Time, which is defined as the travel time of the tour with the current activity included minus the travel time without the activity The travel time is calculated using network level of service data by mode, where a composite mode travel time that accounts for average mode shares is used when the mode is not known For example, the deflected travel time for the shopping trip shown in Figure 12(a) would be the travel time from Home-Shop-Work minus the travel time from Home-Work, or the extra travel time imposed by the inclusion of the activity A second stratification variable is a simple measure of attractiveness of each zone defined by the overall employment level in that zone So the set A is split into subsets A_{ij} where i indexes the travel time strata from 1 to I and j indexes the employment strata from 1 to J, where an equal number of zones are selected into each strata The probability of a zone k being selected into the choice set if it is in the available set can then be defined by

$$p(k) = \frac{N_C}{I+J}\left(\sum_i \sum_j \delta_{ij}/|A_{ij}|\right), \quad 0 < p(k) \leq 1 \tag{17}$$

Where,

N_C = size of choice set

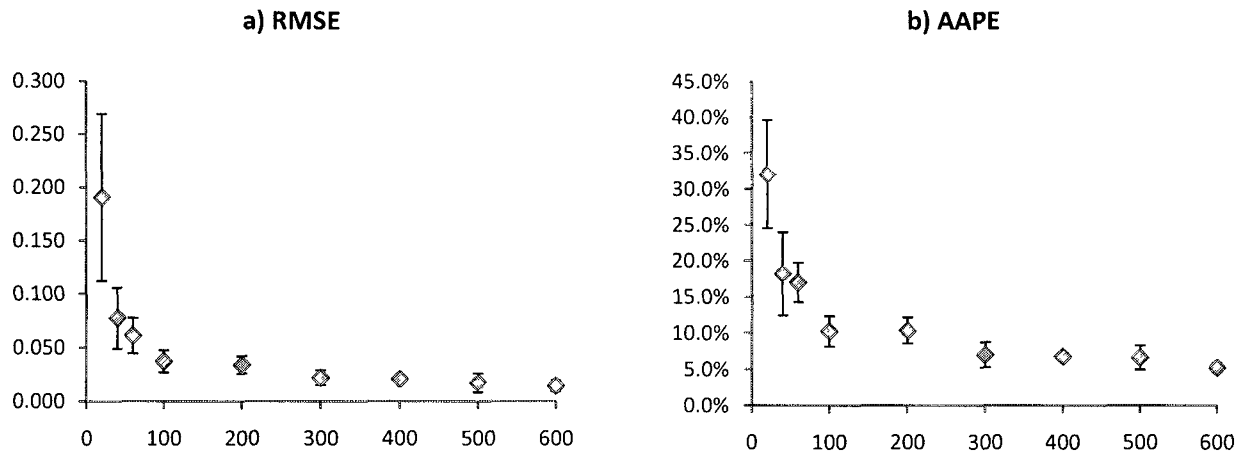
$|A_{ij}|$ = number of zones in subset A_{ij}

$$\delta_{ij} = \begin{cases} 1, & k \in A_{ij} \\ 0 & \end{cases}$$

This process of importance sampling of the alternatives in the *Available Set* defined by the planning constraints to develop the choice set provides for a more realistic choice set as closer and more attractive zones are oversampled relative to more distant and unattractive zones, although the process does introduce sampling bias to the model (Ben-Akiva and Lerman, 1985), which needs to be accounted for in the model specification Additionally, other important factors for consideration in choice set formation are the final size of the choice set (and each strata within the choice set) and the consistency of the parameter estimates obtained using the reduced choice set These issues are investigated next

10.2.2 Choice Set Size and Parameter Consistency

An important consideration in the development of the model is the size of the choice set from which individuals make their final selection Smaller choice sets are easier to simulate, but too-small choice sets produce inconsistent parameter estimates. Therefore it was necessary to determine the smallest possible choice set size which produced consistent parameter estimates. An analysis was performed using the model described in the following sections to determine the optimal choice set size. The results of this analysis are shown in Figure 13 below. In the analysis, the root mean squared error and average absolute percent error for the parameter estimates obtained from model runs using a range of choice set sizes (from 20 to 600 maximum choice set size) are calculated against parameter values obtained from using the full "available set" as the choice set for each choice observation. Note that each observation is shown as the average and +/- one standard deviation of a number of model runs to account for the variance from the stochastic choice set selection. The analysis is only shown for the "Shopping" activity although other activity types follow a similar pattern.



Max Choice Set Size	20	40	60	100	200	300	400	500	600
Avg Choice Set Size	16.0	28.8	40.3	59.3	97.5	129.7	159.4	187.2	210.767
Avg of (Choice / Available)	26.9%	34.5%	39.6%	45.8%	54.5%	59.7%	63.8%	67.1%	81.7%
Avg Choice / Avg Available	2.3%	4.2%	5.9%	8.7%	14.3%	19.0%	23.4%	27.5%	30.9%

Figure 13. Destination Choice Set Size Analysis

The results of the analysis show that initially there is a large error in the parameter estimates when the choice set size is small. However the error decreases rapidly as the maximum choice set size increases and levels off somewhere around 100 zones. The table below the figures shows some statistics regarding each maximum choice set size. Note that the average realized choice set size is never as large as the maximum due to the stratification scheme used, i.e. for a choice set size of 100 there are 4 strata with a maximum of 25 zones in each. However, as the maximum size increases some strata become harder to fill (i.e. low travel times) so the choice set size never reaches the maximum. At a maximum size of 100 the average choice set consists of 59 zones. At this size, the average choice set comprises approximately 46% of the available choice set. Based on these results a choice set size of 100 zones was selected. Next, the specification for the model used in the above analysis is described.

10.2.3 Model Specification

The destination choice model for each activity type is specified as a standard multinomial logit (MNL) model with several additions. These additions include the use of competing destination terms as described in Fotheringham et al (1983), which were originally intended to mimic the processing of zones from the universal choice set into those zones which were actually considered. These terms represent an addition to the utility function which increase or decrease the utility of a zone based on its accessibility to nearby competing (or cooperating) destinations. The competition terms in Equation 18 differ from the standard competing destinations model as they are not log-transformed in the utility function and also include a parameterized distance decay function which is explicitly solved for rather than assuming linear distance decay. The model is similar to that developed by Bernardin et al (2009) in that it includes competition and agglomeration effects (depending on the sign of the θ parameters) and explicit inclusion of the distance decay parameter. Note that the zonal size variables, including the land-use and employment by various categories, enter the utility function as a log-sum in order to maintain proper zonal probabilities regardless of boundary formulations (Daly, 1982; Pozsgay and Bhat, 2002). The formula for the systematic portion of utility, for zone i and decision-maker n, is given in Equation 18.

$$V_{in} = \beta_T T_{in} + \beta_I ln(I_{in}) + \beta_R R_{in} + \gamma \ln\left(\sum_j^J \beta_j A_{ij} + \sum_k^K \beta_k E_{ik}\right) + \sum_k^K \theta_k C_k + \ln\left(\frac{1}{p(i)}\right) \tag{18}$$

Where,

β_T = travel time parameter

T_{in} = travel time to zone i from home location of decision-maker n

β_I = income difference parameter

I_{in} = absolute value of average zonal income for i minus income for decision-maker n

β_R = race difference parameter

R_{in} = 1-R_i, where R_i is the percentage of residents of zone i of a different race than decision-maker n

γ = logsum parameter for zonal size variables

β_j = parameter for the j=1...J, land use variables

A_{ij} = values of the j=1...J, land use area variables for zone i

β_k = parameter for the k=1...K, employment sector variables

E_{ik} = values of the k=1...K, employment sector variables for zone i

θ_k = competition/clustering parameter for employment variable k

C_k = Competition/Agglomeration factor, see Equation 19

$p(i)$ = probability of selecting zone i into the current choice set, from Equation 2

The competition/agglomeration factor for each employment category is defined as shown in Equation 19.

$$C_k = \left(\frac{1}{N_z - 1} \sum_{l \neq i}^{N_z} E_{lk} e^{\gamma t_{il}}\right) \tag{19}$$

Where,

N_z = number of zones in region

t_{il} = distance between zone i and another zone l

γ = distance decay parameter

This factor is approximately equivalent to the average accessibility of all other zones to the current zone weighted by the employment variable E_{lk} in the other zones. This factor is higher for zones which are more accessible to surrounding employment categories, and measures, in effect, how clustered the current zone is with different surrounding employment types.

This utility specification was combined with the choice set formation procedure to estimate a destination choice model for seven discretionary activity types in the Chicago region as described in the next section.

This utility specification was combined with the choice set formation procedure to estimate a destination choice model for seven discretionary activity types in the Chicago region as described in the next section.

10.3. Data Sources

The destination choice model has been developed for the Chicago region using the 2007 Travel Tracker Survey *(*CMAP, 2007*)*, which was an activity-travel survey of 10,552 households over one or two days, producing data on 61,267 non-mandatory activities. This has been combined with land use data (CMAP, 2010a) overlaid onto the regional traffic analysis zone system. This analysis focused on seven major classes of non-mandatory activities including Major Shopping, Minor/Grocery Shopping, Eating Out, Recreation/Entertainment, Social, Services/Healthcare and Religious/Civic Engagement. The average of the model variables for the selected zones by each activity type is shown in TABLE XII.

TABLE XII
AVERAGE VALUES OF VARIABLES FOR SELECTED ZONES

Variable	Services	Minor Shop	Major Shop	Eat Out	Rel / Civic	Rec / Entertain	Social
Travel Time	26.97	17.17	20.98	21.67	24.14	26.85	30.03
Log (d_Income)	10.22	10.21	10.23	10.24	10.24	10.28	10.21
d_Race	0.28	0.28	0.26	0.27	0.25	0.27	0.26
Resid. Area (mmsf)	21.4	21.2	23.2	20.2	21.4	21.9	22.5
Rec. area (mmsf)	6.1	5.6	7.3	5.8	5.8	6.6	6.9
Retail area (mmsf)	0.4	0.7	1.0	0.5	0.2	0.4	0.3
Entertain area (mmsf)	0.3	0.3	0.3	0.3	0.3	0.4	0.3
Institutional area (mmsf)	1.4	1.1	1.1	1.1	1.2	1.2	1.2
Office area (mmsf)	0.5	0.6	0.9	0.6	0.2	0.5	0.4
Mixed use ares (mmsf)	2.2	2.4	2.6	2.3	2.1	2.2	2.0
School area (mmsf)	1.2	1.0	1.1	1.0	1.3	1.2	1.2
Other Emp. (000s)	0.40	0.37	0.40	0.42	0.31	0.38	0.32
Government Emp. (000s)	0.64	0.36	0.34	0.53	0.45	0.49	0.46
Service Emp. (000s)	2.25	1.68	1.77	2.30	1.52	2.13	1.54
Retail Emp. (000s)	0.67	0.82	0.96	0.79	0.50	0.74	0.54
θ gov	1.69	1.26	1.31	2.28	1.12	1.72	0.99
θ manufacture	0.91	0.82	0.83	1.08	0.73	0.91	0.71
θ retail	1.21	1.06	1.13	1.50	0.89	1.25	0.85
θ service	6.58	4.95	5.34	9.11	4.08	6.97	3.64
θ industrial	0.94	0.78	0.83	1.17	0.68	0.93	0.64
θ other	0.97	0.80	0.84	1.26	0.68	1.00	0.63

10.4. Model Results

The destination choice models for each activity type have been estimated using the Chicago Travel Tracker data as described in the previous sections. In addition to the planning constrained destination choice models a second set of destination choice models have been estimated for comparison purposes. The second set of models is estimated using choice sets formed only with routine, fixed activity constraints, without considering any activities in the schedule which may have been preplanned but are not routine. This model will be referred to as the "Non-planning constrained" model through the remainder of this chapter. Parameter estimates for the constrained model are shown in TABLE XIII.

TABLE XIII
DESTINATION CHOICE MODEL RESULTS FOR CONSTRAINED MODEL

Parameter	Services	Minor Shop	Major Shop	Eat OutR	el/Civic	Rec/Entertain	Social
Travel Time	-0 068	-0 085	-0 060	-0 064	-0 068	-0 067	-0 059
Log (d_Income)	0 016	–	-0 113	-0 110	-0 096	-0 073	-0 101
d_Race	-1 190	-0 405	-1 020	-0 857	-2 020	-1 040	-1 530
Ln (Area_resid)	–	–	–	–	–	–	0 106
Ln (Area_rec)	0 045	–	–	0 020	–	0 109	0 051
Ln (Area_retail)	0 022	0 058	0 045	0 036	0 013	–	0 019
Ln (Area_ent)	–	–	–	–	0 011	0 024	–
Ln (Area_inst)	0 023	0 032	0 062	0 027	0 073	0 035	0 038
Ln (Area_office)	0 013	–	–	–	–	–	–
Ln (Area_mix)	0 033	0 038	–	0 055	0 027	0 041	–
Ln (Area_school)	0 036	–	–	–	0 098	0 033	–
Other Emp (000s)	–	0 301	–	–	–	–	0 439
Government Emp (000s)	0 111	–	–	–	–	–	0 089
Service Emp (000s)	0 091	–	–	0 036	0 122	0 016	0 023
Retail Emp (000s)	0 129	0 272	0 576	0 269	–	0 290	0 119
θ gov	–	-0 053	0 332	–	–	–	0 068
θ manufacture	–	-0 024	–	–	–	–	–
θ retail	–	-0 028	0 342	-0 085	-0 118	-0 117	-0 131
θ service	–	–	-0 127	–	–	0 026	–
θ industrial	–	-0 108	–	–	–	-0 092	-0 096
θ other	-0 079	0 147	–	–	–	–	–
Gamma	-0 29	-0 40	-0 18	-0 25	-0 18	-0 40	-0 33

This table shows how the major independent variables impact the destination choice decisions for each activity type. The travel time and race difference parameters are always negative and the income difference parameter is almost always negative, showing that these variables have a negative impact on choice probabilities as expected. The attraction variables all have positive impacts for both models. The competition/agglomeration parameters, meanwhile, have a more varied impact, sometimes showing agglomeration effects and sometimes competition effects, and the results are often different between the plan constrained and unconstrained models. Finally the gamma parameters from the distance decay in the accessibility equations have also been estimated. Note that a common gamma parameter is estimated for all competition equations for each activity type to simplify the model estimation.

10.4.1 Response Elasticities for Selected Variables

Direct comparisons of parameter impacts on each destination choice model are difficult to make simply by comparing the estimated parameter values between models for a variety of reasons, mostly relating to potential scale differences between the different activity types. Therefore, to compare the impact different model variables have on the activity types, the direct elasticity for the variables are instead compared for the planning constrained model.

Unfortunately, determining an average elasticity of destination choice models for given variables is not particularly straightforward for a number of reasons, the most important of which is that there is no definition of an average choice set at which to evaluate the elasticities, as every chooser faces a different set of zones. So in reality, the actual elasticities for a chooser are highly dependent on the choice set composition, and even for which choice within the choice set the elasticity is calculated for. If a zone is a clearly dominant or clearly inferior choice in the choice set, the elasticities will be much smaller than if the zone falls somewhere in between, a well documented property of the logit formulation. Therefore, to get around these issues, for each activity type the average properties of all the selected zones for that type are calculated and a choice set composed of one hundred identical copies of this zone is created for purposes of elasticity calculations. Because all of the choices are identical this gives a base probability of 1%, which falls on the lower end of the logit curve, so in fact some of the elasticities presented will likely be underestimates of true elasticities for clearly dominant zones, however they should be fairly representative. With this choice set specification the elasticities are then calculated using the formula in Equation 20 for the linear in terms and Equation 21 for the log-transformed terms.

$$E_{\iota,x} = \beta_x x_\iota (1 - p_\iota) \tag{20}$$

$$E_{\iota,x} = \beta_x (1 - p_\iota) \tag{21}$$

One simplification in this procedure, however, involves the competition terms, as in reality a change in the competition term for one choice will almost always involve changes in competition terms for the other choices. This would mean that Equation 20 cannot be used to calculate the utility with respect to the competition terms. Therefore an assumption is made in this analysis that the competition increase for each choice occurs without impacting the other choices, in which case Equation 20 can be used. While this result may seem to overstate the value of elasticity with respect to the competition term, the model is applied to a fairly small random selection from the total set of zones and these random selections are not necessarily near each other so that in many cases an increase in accessibility for one zone may not mean an increase for the other zones in the set, which may mitigate this issue to a degree.

The elasticity estimates for several significant model variables, including the travel time, race and income difference, retail employment, retail area and retail accessibility (competition), are shown in Figure 14 from a decrease of 20% to an increase of 20% of each independent variable. The figures show the elasticities with respect to the selected independent variables for the seven main categories of discretionary activities, which give a clearer picture of how the variables impact each model rather than using a comparison of the parameter values alone. For example, it is clear from Figure 14(a) that Major Shopping activities are far less sensitive to travel time than are Recreation/Entertainment activities with elasticities of -1.5 and -2.0 respectively, meaning that an increase in travel time to a zone of 1% would be expected to cause a decrease in probability of choosing that zone of 1.5% for a major shopping activity but 2.0% for a recreational activity. This, however, would not be immediately clear from the parameter estimates of -0.06 and -0.068 respectively. The result is reasonable as it seems likely that individuals would be more willing to accept longer travel times when travelling to make a major purchase than when traveling for recreation, since major purchases are largely influenced by economic considerations (i.e. trading off travel time for lower prices).

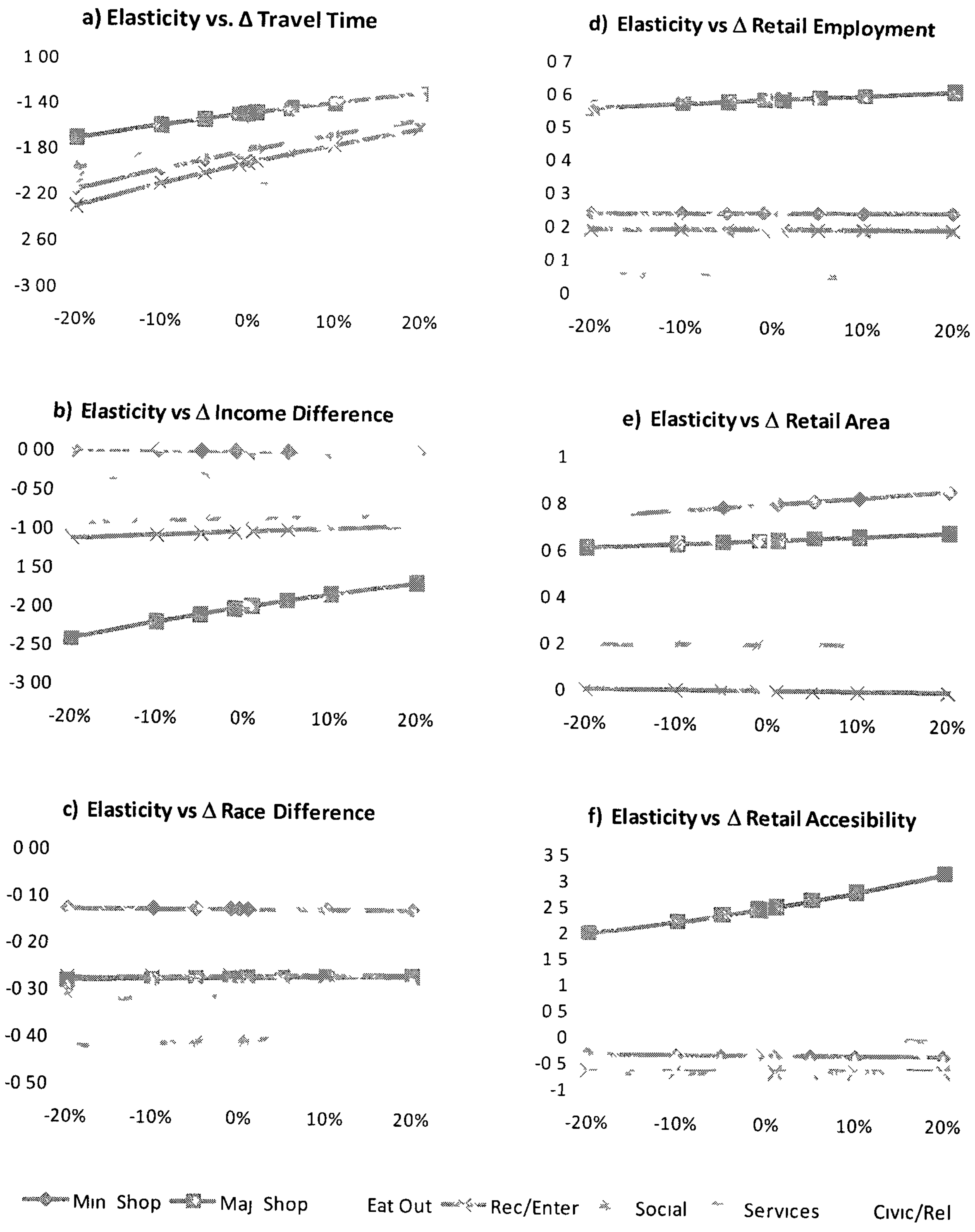


Figure 14. Elasticity versus percentage change in Model Variables
(a) Deflected Travel Time (b) Income Difference (c) Race Difference
d) Retail Employment (e) Retail Area (f) Retail Accessibility

The elasticity estimates for the variables all show meaningful and theoretically sound results. All activities show a highly elastic negative response to changes in travel time, while most of the activities show slightly inelastic to highly elastic responses to differences in income, especially for the major shopping activity. The highly elastic response of the major shopping activity to income difference makes sense as individuals are less likely to make major purchases in zones which generally serve residents in different economic strata. Most activities are less sensitive to differences in zonal racial composition from the decision maker's race, but those activities which are most sensitive to this term are the social activities, such as socializing, religious and civic engagement. The remaining three variables all relate to measures of retail attractiveness and as expected they mainly impact the shopping activities, and to a lesser extent other activities such as eating out and services which can to some degree overlap with retail employment/land use. The shopping trips have stronger, though still inelastic, positive responses to increase in retail employment and area than the other activity types have. Finally, the retail employment competition term has little impact on all of the activity types except for the major shopping activity where it has a positive strongly elastic impact. This shows that individuals tend to look for shopping districts where retail zones have clustered around one another when making major purchases, such as shopping malls, downtown shopping districts, etc.

10.5. Destination Choice Validation

In order to validate the use of activity planning constraints in the estimation of the destination choice model, the results of the planning constrained model were compared against results from the non-planning constrained model described previously in a number or ways. However evaluating the validity of models of this type is difficult as the traditional means of comparison – evaluating and comparing the respective increase in log likelihood, or the likelihood ratio, for each model – is uninformative as the differences between the models lies only in how the choice set is formed. For this reason, different comparison metrics are needed.

The first comparison used to evaluate the performance of the planning-constraints in destination modeling was to look at the overall model accuracy, or percent correctly predicted, at the disaggregate level. In order to perform this comparison, both the planning-constrained and non-constrained models were applied to the CMAP survey data. Destination choices were estimated for each activity observation and compared to the actual choices. The correct predictions for each model were then compared and also compared against the expected null model results obtained through assuming equal likelihood of all zones within the available set for each situation. This comparison represents an estimate of the disaggregate accuracy of the model, which due to the nature of destination choice and the large number of choices, is naturally somewhat low. An aggregate-level comparison then, was also performed, where the destination choices for each activity were aggregated to the zone level and compared against the observed zone level counts. An R^2 measure between the simulated and observed counts for each model was then estimated for comparison.

In both comparisons performed, the planning constrained model outperforms the unconstrained model, and well outperforms the null model expectation (calculated from the available set size for each choice situation). The planning constrained model correctly predicts 8.5% (σ = 0.04%) of destination choice TAZs, while the unconstrained model only correctly predicts 6.0% (σ = 0.02%) of choices, averaged over 10 model runs, and both are significantly higher than the null model expectation of 2.7% correct predictions. For the aggregate zone level counts, there is an R^2 of 0.578 (σ = 0.005) for the plan constrained model results to the actual counts compared against a value of 0.518 (σ = 0.003) for the unconstrained model. The planning constrained model significantly outperforms the unconstrained model in both measures, as expected.

A final validation performed was the comparison of the trip length distributions resulting from the application of the planning-constrained and non-planning constrained models to the CMAP survey data to the observed trip length distributions. The results can be seen in Figure 15 which shows each distribution. It is clear from the figure that the planning-constrained model fits much more closely to the observed data than does the non-constrained distribution. The non-constrained model greatly underestimates the number of short distance trips and overestimates the number of trips in the 20 – 60 minute range. The constrained model, meanwhile, exhibits these tendencies to a much less pronounced degree. The results show that not considering constraints imposed by activity planning can bias aggregate results.

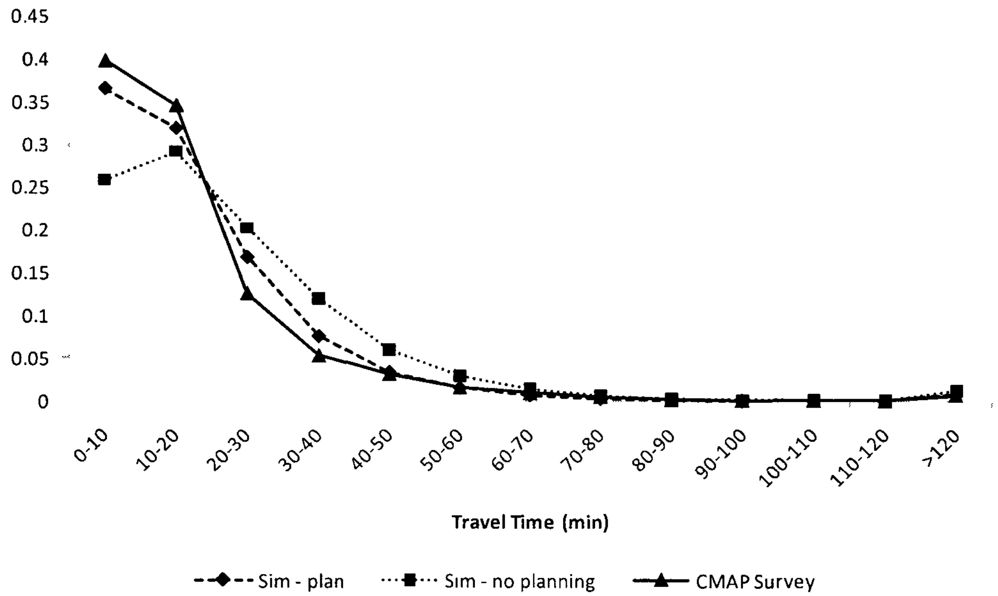


Figure 15. Observed and simulated trip time distributions with and without planning constraints

10.6. Destination Choice Model Conclusions

The destination choices of individuals represent perhaps the most significant influence on their overall travel demand making destination choice models critical component of all advanced disaggregate travel demand models. As activity-based travel demand models grow more advanced, especially in regard to representing the dynamics of activity-travel planning and scheduling, destination choice models will need to adapt. This issue naturally arose during the development of the ADAPTS activity-based model, with the introduction of the concept of activity planning dynamics. To address the issue of dynamics in destination choice, a disaggregate choice model for non-mandatory activities where the choices are constrained by previously planned activities was created. A variant of the competing-destinations multinomial logit model formulation was used to estimate the impact of the travel time, the land use characteristics of the location, the attractiveness in terms of different employment types, socio-economic differences, and a competing destinations term meant to represent the behavioral influence of clustering/agglomeration on destination choices.

The destination choice model for non-mandatory activities was estimated using the recently collected 2007 CMAP Travel Tracker Survey data (CMAP 2007), combined with the results of a previously estimated activity planning model estimated through the use of the 2009 UTRACS activity planning survey. The results of the model estimation show that the model performs well, with an acceptable improvement in percent correct predictions over null model expectation (8.5% against 2.7%), which was also an improvement over the non-planning-constrained version of the model which did not consider preplanned activities in the formation of the choice set. The estimated model was then applied to a synthetically generated population for the region created to match known population characteristics. The results of the application to the synthetic population were then used to validate the model in terms of trip length distributions and final zonal attraction counts. The results show that the model works well in replicating the trip length distributions observed in the travel tracker survey. The model also replicates the aggregate measure of the expected attraction counts by zone to a high degree of accuracy, demonstrating the usefulness of the model.

Future work on the destination choice model will focus on improving the model formulation to account for the effects of individual heterogeneity and the correlations between zones which naturally arise in spatial contexts and occur in addition to the systematic correlations already addressed through the competition factors. These issues can both be addressed by transitioning from a MNL framework to a mixed-logit (ML) formulation. The mixed-logit model involves making different distributional assumptions regarding the random component of utility than for the simple MNL model. For example, to account for the correlation between zones (spatial autocorrelation), the error can be considered a combination of the IID random term and another random term arising from a Spatial Autoregressive (SAR) process as in Bolduc et al (1996). In a similar manner, the parameters in the model could vary randomly over individuals rather than having a single fixed value by adding random error components to the parameters which results in the Random Parameters formulation of the ML model (Ben-Akiva et al. 2001). In any case, extensions of the basic model developed here to address these issues should result in a more accurate and meaningful representation of the destination choices of individuals.

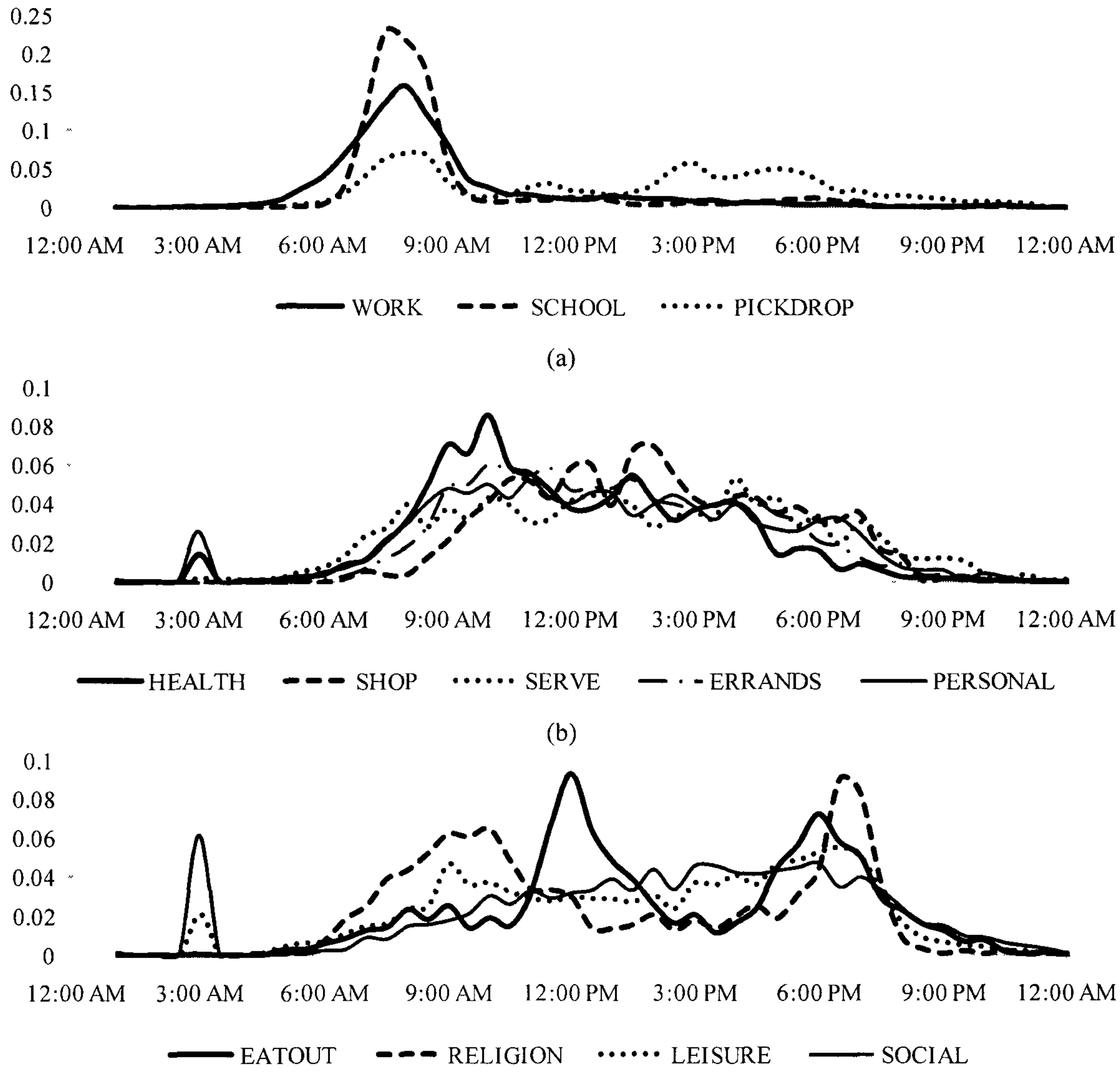
10.7. Other Attribute Models in ADAPTS

The destination choice model in ADAPTS is the only activity attribute planning model that has been fully implemented in a planning constrained manner, as described above. In the future, it is expected that all of the remaining activity attribute choice models will be developed in a similar fashion. This would mean that all of the models will either have plan-constrained choice sets, as was done for the destination choice, or will include the state of the other attributes directly in the choice models. The remaining attribute models in the current ADAPTS system then are placeholders for more advanced models still in development. The remainder of this chapter documents the current state of each primary attribute model in ADAPTS.

10.7.1 Start Time and Duration Models

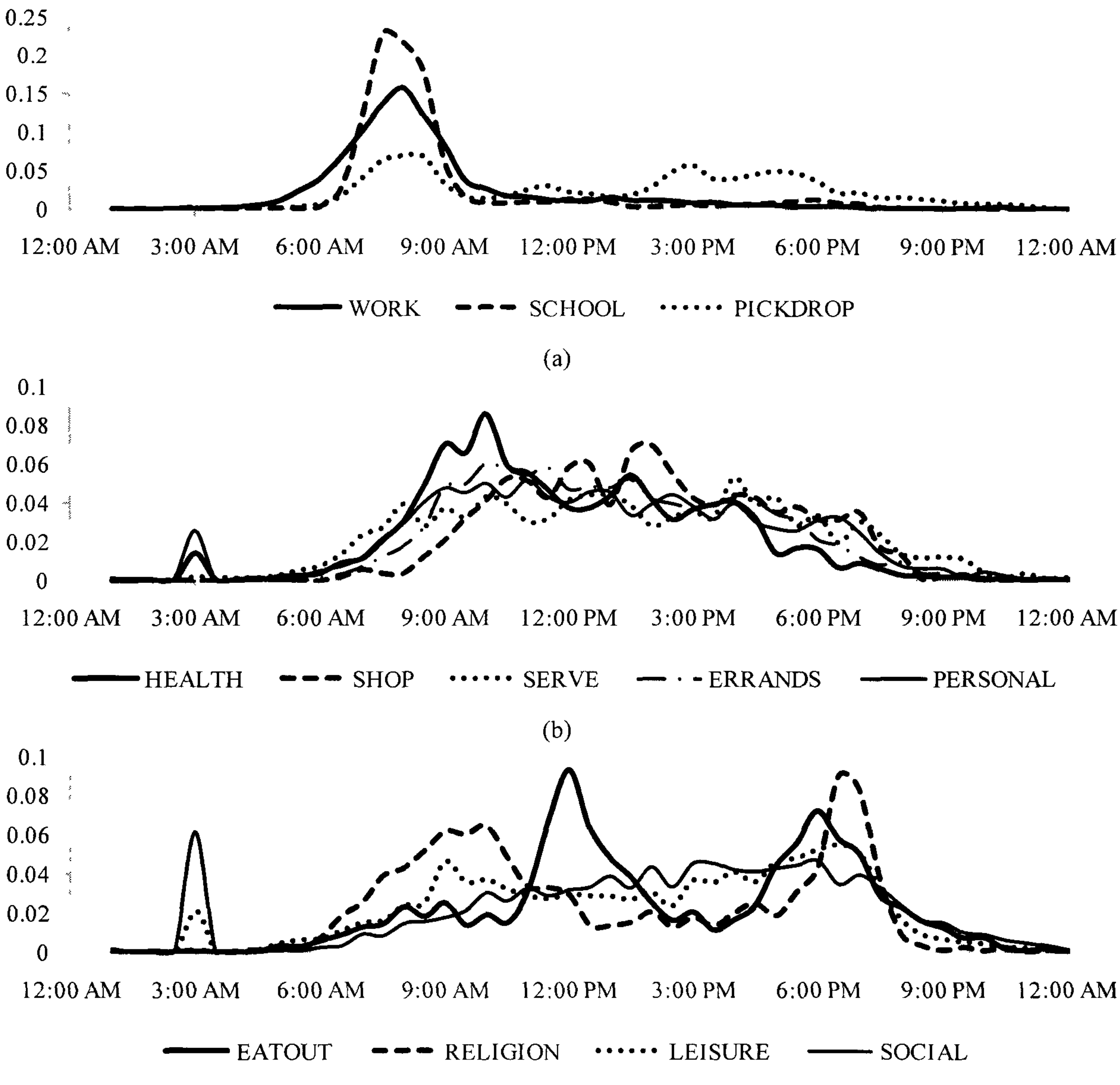
The start time and duration models in ADAPTS are based on probabilistic draws from observed start-time duration distributions. The distributions for each activity used for the random draws are taken from the CMAP Travel Tracker Survey, with some modification to account for split activities. In the case of split activities, the travel survey data is searched for patterns where a long activity, such as a work episode, would be split into two or more shorter episodes by intervening activities. In this process, patterns of long-duration activities occurring in the same location surrounding one other activity, or multiple short activity episodes are considered as one episode for the purposes of start time and duration draws. This is done due to the way activities are scheduled in ADAPTS, with longer duration activities able to be split by smaller activities. If the split-activity correction was not made too many short duration activities would be scheduled in the model. The distributions are also split into separate distributions for employed and unemployed individuals to account for the differences in start times caused by the work activity. The final combined marginal distributions for start time and duration are shown in Figure 16 and Figure 17.

Although there is no model currently underlying the start time and duration attribute selection other than a simple employed versus unemployed heuristic, there is still basic elements of planning constraints, in that the selection of the start time or duration changes depending on which is planned first. This is handled through the use of a joint start-time and duration distribution, where if one attribute is already planned the distribution for the other attribute is restricted to the marginal distribution with the first attribute fixed. Additionally, the fixities of the various attributes also determine how the final start time is selected, through the use of an activity chaining heuristic. The activity can be shifted from its scheduled start time up to a set amount in order to form a tour with another already planned activity, where the time shift is dependent on the start time flexibility. Inflexible activities can be shifted only 15 minutes, while moderately flexible activities can be shifted up to an hour and highly flexible activities can be shifted up to two hours, to take advantage of trip chaining efficiencies. This heuristic introduces some effect of dynamics on the start time planning, but a full start-time duration model is still needed which considers the current state of the activity schedule and of the activity itself when choosing a time.



(c)

Figure 16. Activity Start Time Distributions for (a) Mandatory (b) Maintenance and (c) Discretionary Activities



(c)

Figure 17. Activity Duration Distributions for (a) Mandatory (b) Maintenance and (c) Discretionary Activities

10.7.2 Mode Choice Model

The mode choice model currently implemented in ADAPTS was adopted from the CMAP regional travel demand model (CMAP 2010b). The mode choice model is a logit-based model which currently accounts for three mode types: auto-drive, transit and non-motorized. The non-motorized mode was added to the original CMAP model to account for walking and biking for short trips when auto-mode was unavailable. Simplified planning constraints exist in the mode choice model in several ways. First, if the location is not known, average travel times by activity type are used when making the mode choice. If the location is known, however, the travel time and cost data are determined from the network skims which break down the times into various components. Also, a known location determines which set of coefficients to use in the choice model, as different coefficients are used for CBD and non-CBD destined trips. The timing also places constraints on the available modes in the form of choice-set planning constraints. If the start time and duration of the activity are known, the schedule can be examined to determine the available time around the activity, which can limit transit and non-motorized mode options. If the timing is known, the tour context can be determined which also limits mode availability. The schedule information allows auto and bicycle availability factors to be determined, where if an individual leaves the house without an automobile, the auto mode will not be available until returning home. The model parameters used for mode choice are shown in TABLE XIV.

TABLE XIV
MODE CHOICE MODEL COEFFICIENTS

Variable	CBD Trip	Mandatory Trip	Non-Mandatory Trip
In-vehicle time	0.0159	0.0186	0.0114
Headway	0.0173	0.0811	0.0610
Transfer time	0.0290	0.0399	0.0589
Walk time	0.0486	0.0584	0.0663
Cost	0.0085	0.0072	0.0329
Coefficient	-1.0000	-2.0000	-1.9000

The differences in attribute values for each mode are used as the variables in a standard logit model, as shown in Equation 16, to determine the probability of taking transit. If, however, the auto-mode is unavailable, the auto-mode option is replaced with the non-motorized mode, which then competes against the transit mode. Eventually, the mode choice model is intended to extend to different modes, differentiating between rail and bus, for example, and will be re-estimated considering planning constraints in the same manner as was done for the destination choice models.

10.7.3 Party Composition Models

Currently, party composition modeling is not implemented in ADAPTS, other than scheduling pick-up and drop-off activities for parents and their children. The pick-up and drop-off activities are scheduled by first determining if the child is old enough to attend activities alone. This decision is based on the age of the child and the distance to the school or other activity location. If it is determined that a parent is needed to escort the child, the activity scheduler looks through the household member schedules to determine if anyone is available and has a vehicle at the requested time. If no one is available, a high priority conflict request is made, where the conflict resolution and scheduling process (discussed in the next chapter) attempts to add the escort activity to the least occupied individual. If this is successful, the pick-up / drop-off activity is added to the individual schedule as a high priority activity (meaning it cannot later be modified), and the original activity is added to the child's schedule. If the addition is unsuccessful, both the escort activity and the original activity are dropped.

The models described in this chapter represent the current state of attribute planning in the ADAPTS model system. The attribute models are all intended to incorporate the concept of "planning constrained" choices, where the plan time influences the final outcome. All of the models utilize this concept to some extent, however, only the destination choice model has been fully estimated as a planning constrained model. After all of the attributes of an activity are planned, it can be added to the activity schedule. This process is described in the following chapter.

11. ACTIVITY SCHEDULING AND CONFLICT RESOLUTION

11.1. Introduction to Activity Scheduling

Computational Process Models such as ADAPTS require some ways to handle activity scheduling and conflict resolution due to the nature of the activity-schedule building process. In these models, predefined sets or tours of activities are not chosen, but rather activities are generated and added to the schedule as needed, which naturally can generate scheduling conflicts as in the real-life scheduling process it is intended to mimic. In the past few years an increasing number of studies have been conducted on estimating scheduling process behavior from actual scheduling process data. Mohammadian and Doherty (2006) developed a model to estimate the planning time horizons for preplanned activities. Ruiz et al. (2005), and Ruiz and Timmermans (2006) have estimated a variety of models for activities inserted between pre-planned activities that consider timing and duration changes to the originally planned activities. Ruiz and Roorda (2008) have estimated models of the incidence of various decisions relating to the activity scheduling process. Finally, Joh et al. (2005) evaluated the factors effecting schedule modification again using scheduling process data.

Conflict resolution is generally an important process in the actual underlying scheduling process and in CPM-type activity-based models which attempt to represent this process of activity schedule creation. However, data describing the actual dynamic process behind activity scheduling has historically been lacking. Therefore most operational models which consider conflict resolution and rescheduling, such as SCHEDULER (Garling et al. 1994) and TASHA (Miller and Roorda 2003), have tended to do so in an ad hoc fashion, with resolution involving a number of assumptions and estimations rather than based on actual data. An exception is the AURORA model, an extension to the ALBATROSS, which explicitly models short term activity scheduling and rescheduling decisions using utility maximization (Joh 2004). However, this model is an econometric model estimated from a diary data rather than scheduling process. As more sources of activity scheduling process data become available, more realistic models of many of these dynamic processes will be possible. Current sources include the Computerized Household Activity Scheduling Elicitor or CHASE© survey (Doherty et al. 2004), REACT! (Lee and McNally, 2001) and surveys by Ruiz and Timmermans (2006), Clark and Doherty (2008) and others.

Currently implemented models of activity scheduling processes based on process data within activity scheduling models are rather limited. The scheduler for ADAPTS implements a conflict resolution model (Auld et al. 2008) within a set of scheduling rules derived from the TASHA scheduling framework. The ADAPTS scheduling rules are then tested against a reimplementation of the TASHA scheduling rules using the CHASE activity survey data. The results of each scheduler are compared against the executed activity patterns from the CHASE dataset using a simplified time-sequence alignment measure. This section is structured as follows. Section 2 provides a brief overview of the data source used in the conflict model and scheduler comparisons. Section 3 details the development of the conflict resolution model. Section 4 documents the activity scheduling rules in TASHA and in the updated scheduler. Section 5 describes how the CHASE data has been prepared and used to evaluate each scheduling routine. Section 6 discusses the sequence alignment measure that was used for scheduling comparison. Section 7 presents the results of the comparison between each system. Finally, Section 8 presents the significant findings from the analysis and opportunities for future work.

11.2. Data Source for Conflict Resolution and Scheduling Comparison

Since the comparison performed for this analysis is meant to determine how accurately each scheduling rule system can replicate the actual scheduling process, a dataset which contains both the initial plans and the realized results of the scheduling process was needed. For this reason the CHASE dataset (Doherty et al. 2004) was used, as it remains one of the few sources of scheduling process data. CHASE is a seven day computerized activity diary survey conducted in Toronto, Canada. A total of 271 households were interviewed and participants' activities and travel patterns were recorded on a laptop. Many detailed questions about flexibility of activity in time, space, interpersonal, and travel mode were asked. The program tracks when and why the various scheduling decisions are made, and displays to users the results of their scheduling efforts in the form of observed activity-travel patterns. Users are asked to add, modify and delete activities anywhere on their schedule as their plans evolve over a multi-day period. The final state of their activities on screen is taken as observed patterns, replicating what is captured by traditional activity diaries. A detailed description of the design and conduct of this survey, characteristics of the sample, and data quality can be found in Doherty et al. (2004).

11.3. Development of an Activity Scheduling Conflict Resolution Model

11.3.1 Finding Conflicts in the CHASE Dataset

For this study, conflicts were defined as a situation in the schedule when two activities are planned which overlap in time and can therefore not both be executed as originally planned. Note that this definition explicitly excludes instances of multi-tasking, which was allowed in the CHASE survey, since if both tasks can be executed no conflict can be said to have occurred. Unfortunately, activity conflicts can only be inferred from the observed data since no direct observation of conflicts was made during the survey, i.e. the user was not asked if a modification was being made due to a scheduling conflict of for some other reason. To correct for this occurrence, a threshold of one hour was used between the modification of an existing activity and the addition of the new activity, as was done in the analysis by Roorda et al. (2005b). Therefore, any new activity which overlapped the space left by a deleted or modified activity but was added over an hour later was not considered a valid conflict.

In order to identify conflicts in the dataset, a conflict finding algorithm was first created. This process determines whether any two activities were in conflict in time then checks if the activities were actually different activities, or two instances of the same activity. Figure 18 shows the conflict types that can be generated. Type 1 and Type 2 conflicts are edge conflicts, where the conflicting activities partially overlap either the start or end of the original activity. Type 3 conflicts occur when a small conflicting activity is inserted within the original activity, and Type 4 conflicts occur when the original activity is entirely overlapped by a larger conflicting activity.

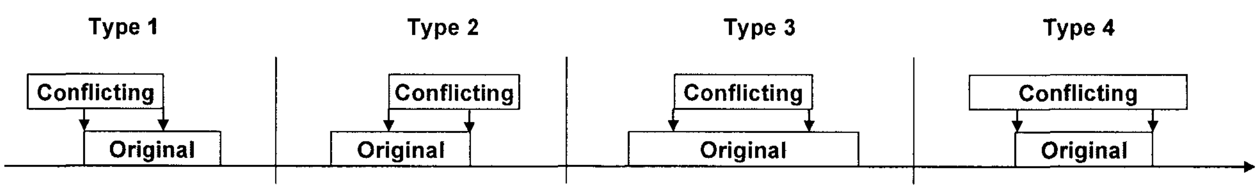


Figure 18. Basic Activity Conflict Types

After the valid conflicts were identified, it was necessary to determine the strategies employed to resolve them. This involved using a set of rules to determine whether a valid resolution to the conflict was made. The rules used to identify conflicts are as follows:

- Identify cases of temporal overlap
- Determine original and conflicting activities based on planning horizon variable
- If only one activity executed – define resolution type based on subsequent modification to other activity
- If neither activity executed – define resolution based on subsequent modifications for both activities
- If both activities executed – not a conflict (multi-tasking), remove from conflict list
- For all conflict pairs – determine if modifications resolve conflict, if not remove from conflict list

It is important to note that the term 'executed' above is defined based on whether the activity record is a final executed activity in the CHASE dataset, not whether the final activity is eventually executed. This is why if an activity conflict is found between two activities that both are 'executed' this means that they actually overlap in the surveyed individual's activity pattern. The purpose of the conflict finding algorithm is to identify conflicts between activities that are not 'executed' but are subsequently modified to resolve the conflict. So usually when a valid conflict is found one of the non-executed activities will have a subsequent modification entry which is executed.

TABLE XV below shows the activity conflicts found in the dataset. As can be seen there are a total of 1425 valid conflicts between 1008 original activities which are overlapped by 1182 conflicting activities. Note that the number of conflicting and original activities is not necessarily equal since one original activity can be overlapped by more than one conflicting activity and vice versa. For the purposes of creating the model, five separate conflict resolution strategies were defined:

- Resolution Strategy 1 (RS1): Modify the originally planned activity ("Modify Original")
- Resolution Strategy 2 (RS2): Modify the conflicting activity ("Modify conflicting")
- Resolution Strategy 3 (RS3): Modify both activities ("Modify Both")
- Resolution Strategy 4 (RS4): Delete the original activity ("Delete Original")
- Resolution Strategy 5 (RS5): Delete the conflicting activity

TABLE XV
ACTVITY CONFLICTS IN THE CHASE DATASET

Conflict Location	Original Activities	Conflicting Activities	Total Conflicts
Out-of-home	548	677	826
In-home	460	505	599
Total	1008	1182	1425

Resolution Strategy 5 is not included in the model since this behavior was not actually captured in the survey There are theoretically a very large number of potential activities which conflict with currently scheduled activities which the user will not enter into the schedule due to their being rejected outright (Roorda et al 2005b) For this reason, the deletion of the conflicting activity is not considered a choice, but rather the default selection if the other four resolution strategies fail It is important to note that the conflict types modeled are an aggregated subset of all of the potential resolution strategies, since moving the activity and modifying the activity are grouped into the same category to reduce the complexity of the model

The conflict resolution strategy distributions where both activities are in home (in-home conflict) versus the conflicts where at least one of the activities is out of home (out-of-home conflict) are shown in Table 2 The in-home conflicts have a lower percentage of conflicts resolved through deletion of the original activity, and a higher percentage of conflicts resolved by modifying the conflicting activity compared to the out-of-home conflicts This shows the more flexible nature of in-home activity rescheduling, and motivates the use of separate in-home and out-of-home scheduling models

TABLE XVI
OBSERVED CONFLICT RESOLUTION STRATEGIES

	Out-of-Home	(%)	In-Home	(%)	Total	(%)
RS1 Modify Original	347	42 0%	321	53 6%	668	46 9%
RS2 Modify Conflicting	106	12 8%	134	22 4%	240	16 8%
RS3 Modify Both	92	11 1%	47	7 8%	139	9 8%
RS4 Delete Original	281	34 0%	97	16 2%	378	26 5%
Total	826	100 0%	599	100 0%	1425	100 0%

11.3.2 Descriptive Analysis of Activity Conflict Attributes and Conflict Resolutions

In order to generate the conflict resolution model, key attributes which are expected to affect the conflict resolution process were first identified, as listed in TABLE XVII These attributes can be classified into three categories

- Individual characteristics, including the person's age, gender, employment status, and number of children
- Activity characteristics, such as the duration, personal and time fixity, location (in or out of home), necessity of travel, number of children involved and planning horizon for each conflicting activity
- Conflict characteristics This category includes the conflict type (shown in Figure 1), the overlap percentage of the original activity, and the amount of time available in the schedule when the conflict occurred

These attributes were thought to be the most likely to influence an individual's behavior The activity characteristics define the activity and generally reflect how necessary and flexible the activity is perceived to be by the individual (see Doherty 2005 for a more detailed discussion/description of fixity variables, Doherty 2006 for planning time horizon) The conflict attributes, meanwhile, determine the feasibility of certain conflict resolution strategies and how they will be employed for certain situations Variable names, description, coding and basic descriptive statistics of the variables used in the model are shown in TABLE XVII for reference

An exploratory analysis of the observed conflict resolution behavior was performed to guide the model development Frequency distributions for the various resolution strategies were evaluated for several of the attribute variables, including the socio-demographic characteristics of the individual, the characteristics of the activity conflict itself, and finally the characteristics of the activities involved in the conflict, including the duration, travel mode of the activities and the planning horizon for each activity, and are shown in TABLE XVIII The frequency distributions were evaluated using chi-squared test for differences in the distributions All of the variables tested were found to significantly impact the distribution of resolution responses The planning horizon and personal flexibility of the activities, as well as the conflict type and percentage overlap, were found to be the most significant

TABLE XVII
DESCRIPTIVE STATISTICS OF CONFLICT RESOLUTION MODEL VARIABLES

Variable	Description	Coding	Avg.	St. dev.
Individual variables				
GEN	Gender	0=male, 1=female	0.640	0.480
SENIOR	Senior indicator	1=over 65	0.140	0.347
EMPIND	Employed indicator	1=employed out of home	0.738	0.440
Original activity variables				
A_PER	Personal Fixity	1=alone, 2=with others, 3=optional	–	–
A_DUR	Duration	Minutes	218.859	247.608
A_LOC	Location	0=in home, 1=out of home	0.395	0.489
ACHILD	Children present	0=no, 1=yes	0.109	0.312
A_TRAVEL	Travel episode required	0=no, 1=yes	.906	0.292
ATIMEF	Time fixity	1=fixed, 2=flexible	1.704	0.457
APLAN	Planning	1=impulsive, 2=same day, 3=preplanned, 4=routine, 999=Unknown	–	–
Conflicting activity variables				
B_PER	Personal Fixity	1=alone, 2=with others, 3=optional	–	–
B_DUR	Duration	Minutes	188.046	252.915
B_LOC	Location	0=in home, 1=out of home	0.375	0.484
BCHILD	Children present	0=no, 1=yes	0.086	0.279
B_TRAVEL	Travel episode required	0=no, 1=yes	0.669	0.471
BTIMEF	Time fixity	1=fixed, 2=flexible	1.769	0.422
BPLAN	Planning horizon	1=impulsive, 2=same day, 3=preplanned, and 4=routine, 999=Unknown	–	–
Conflict/schedule attributes				
OVERLAP	Percentage overlap of original activity	Percentage	0.485	0.422
CONTYPE	Type of conflict	1,2,3,4 (see Figure 1)	–	–
T_AVAIL	Free time in schedule	Minutes	170.920	285.576
CONLOC	Location of conflict	0=home, 1=out of home	0.580	0.494

After evaluating the frequency distributions for the various attribute variables, several interesting patterns were observed. The socio-demographic variables had little impact, while several of the attributes of the conflict and the individual activities, including the amount of overlap, conflict type and planning horizon, played an important role in determining the resolution strategy chosen, as seen in the table. The percentage distributions of the resolution strategies show some general patterns, but the interactions between the variables and the relative importance of the variables cannot be fully determined in this manner. For this reason a multivariate model of how the individual underlying variables influence the resolution strategy is needed.

TABLE XVIII
CONFLICT RESOLUTION EXPLORATORY ANALYSIS

	Resolution Strategy Employed (% in brackers)				
Variable	**Modify Original**	**Modify Conflicting**	**Modify Both**	**Delete Original**	**TOTAL**
Gender*					
Male	222 (43 7)	77 (15 2)	56 (11 0)	153 (30 1)	508 (100)
Female	439 (48 6)	161 (17 8)	83 (9 2)	221 (24 4)	904 (100)
Employment status					
Unemployed	198 (52 9)	68 (18 2)	35 (9 4)	73 (19 5)	374 (100)
Employed	470 (44 7)	172 (16 4)	104 (9 9)	305 (29 0)	1051 (100)
Age*					
Under 65	572 (46 7)	197 (16 1)	117 (9 6)	339 (27 7)	1225 (100)
Over 65	96 (48 0)	43 (21 5)	22 (11 0)	39 (19 5)	200 (100)
Percent Overlap					
<25%	425 (67 2)	42 (6 6)	66 (10 4)	99 (15 7)	632 (100)
25% - 50%	119 (57 2)	16 (7 7)	30 (14 4)	43 (20 7)	208 (100)
50% - 75%	36 (43 9)	7 (8 5)	8 (9 8)	31 (37 8)	82 (100)
>75%	88 (17 5)	174 (34 7)	35 (7 0)	205 (40 8)	502 (100)
Available Time (hours)*					
<0 25	295 (50 4)	87 (14 9)	49 (8 4)	154 (26 3)	585 (100)
0 25 - 1 00	129 (53 1)	38 (15 6)	30 (12 3)	46 (18 9)	243 (100)
1 00 - 2 00	55 (39 3)	33 (23 6)	17 (12 1)	35 (25 0)	140 (100)
2 00 - 4 00	51 (46 4)	25 (22 7)	9 (8 2)	25 (22 7)	110 (100)
> 4 00	138 (39 8)	57 (16 4)	34 (9 8)	118 (34 0)	347 (100)
Conflict Type					
Overlap Start of Original	115 (40 5)	49 (17 3)	25 (8 8)	95 (33 5)	284 (100)
Overlap End of Original	184 (52 1)	37 (10 5)	36 (10 2)	96 (27 2)	353 (100)
Inserted Within Original	327 (70 2)	13 (2 8)	56 (12 0)	70 (15 0)	466 (100)
Overlap Entire Original	42 (13 0)	141 (43 8)	22 (6 8)	117 (36 3)	322 (100)
Original Activity Time Flex.					
Fixed	152 (43 8)	60 (17 3)	48 (13 8)	87 (25 1)	347 (100)
Free	414 (50 2)	160 (19 4)	68 (8 3)	182 (22 1)	824 (100)
Original Activity Personal Flex.					
Conducted Alone	354 (55 6)	89 (14 0)	82 (12 9)	112 (17 6)	637 (100)
Conducted With/For Others	66 (41 8)	43 (27 2)	12 (7 6)	37 (23 4)	158 (100)
Optional	289 (45 2)	126 (19 7)	49 (7 7)	176 (27 5)	640 (100)
Conflicting Activity Time Flex.*					
Fixed	129 (43 3)	59 (19 8)	32 (10 7)	78 (26 2)	298 (100)
Free	492 (49 6)	140 (14 1)	87 (8 8)	272 (27 4)	991 (100)
Conflicting Activity Personal Flex.					
Conducted Alone	266 (46 2)	103 (17 9)	60 (10 4)	147 (25 5)	576 (100)
Conducted With/For Others	94 (45 0)	24 (11 5)	19 (9 1)	72 (34 4)	209 (100)
Optional	297 (48 1)	111 (18 0)	59 (9 5)	151 (24 4)	618 (100)
Original Activity Plan Horizon					
Impulsive	77 (54 6)	35 (24 8)	13 (9 2)	16 (11 3)	141 (100)
Same day	71 (61 2)	36 (31 0)	2 (1 7)	7 (6 0)	116 (100)
Pre-planned	368 (47 3)	51 (6 6)	73 (9 4)	286 (36 8)	778 (100)
Routine	56 (46 3)	40 (33 1)	16 (13 2)	9 (7 4)	121 (100)
Unknown	96 (35 7)	78 (29 0)	35 (13 0)	60 (22 3)	269 (100)
Conflicting Activity Plan Horizon					
Impulsive	391 (55 3)	95 (13 4)	50 (7 1)	171 (24 2)	707 (100)
Same day	130 (49 1)	31 (11 7)	19 (7 2)	85 (32 1)	265 (100)
Pre-planned	91 (26 2)	93 (26 8)	60 (17 3)	103 (29 7)	347 (100)
Routine	24 (57 1)	7 (16 7)	3 (7 1)	8 (19 0)	42 (100)
Unknown	32 (50 0)	14 (21 9)	7 (10 9)	11 (17 2)	64 (100)

* X^2 test significant at 0.05 level; all others significant at 0.01 level.

Not all totals sum to 1425 due to missing values.

11.3.3 Modeling Approaches for Conflict Resolution Estimation

Several different model types were used to evaluate the conflict resolution behavior. For this study it was decided to evaluate both a rule-based system and a model based on the discrete choice framework. One way to model the conflict resolution strategies as a rule-based system is through the use of decision trees, since decision trees represent a set of mutually exclusive and exhaustive rules (Arentze and Timmermans, 2000). Several methods in the machine learning and data mining fields have been developed to estimate the form of the optimal tree including C4.5, CART and CHAID. For the rule-based conflict resolution model, the Exhaustive CHAID algorithm was used (Biggs et al., 1991). The Exhaustive CHAID algorithm is an extension of the earlier CHAID algorithm (Kass, 1990). Both methods follow the same basic procedure to sequentially split the dataset based on the most significant predictor at each node.

To estimate the decision tree model of conflict resolution behavior, the input dataset was first split into training and test (validation) data sets, using a 75/25 ratio. The model is estimated by iteratively splitting each parent node into more homogeneous children nodes by selecting the explanatory variable which gives the highest calculated chi-square statistic for the split (Biggs et al., 1991). The procedure continues until a stopping criteria is reached, which in this model required a minimum of 40 cases for the parent nodes and 20 cases for the leaf nodes, in order to not create rules based on a very small selection of cases. In the development of the decision tree for the model, the estimated tree was often not globally optimized since the split variable at each stage is selected based only on the effects on the next lower level. To work around this problem many different combinations of predictor variables were investigated manually to produce a more optimal tree. The final model was chosen to minimize the misclassification estimates for both the training and test sets and minimize the number of rules created.

Two additional models were estimated using the discrete choice modeling framework for comparison purposes. For this study, both a Multinomial Logit (MNL) and Nested Logit (NL) model were estimated. The discrete choice models were used to evaluate the decisions underlying the conflict resolution choices made. The MNL and NL models differ from the decision tree model in several important facets. Most importantly, the logit-models are based on the theory of random utility maximization, so the discrete choice model selects the alternative that is thought to provide the highest utility to the individual in a given situation. Alternatively, the decision tree model can more easily capture combination effects and non-linear relationships between the explanatory variables. The results and findings for both models are compared in the next section.

11.3.4 Modeling Results

The final conflict resolution model decision trees rules for out-of-home and in-home activity conflicts can be seen in TABLE XIX. The table shows the derived rules that represent the process which individuals use to resolve activity conflicts in their activity schedule. The splits are made in the order that the attributes are presented. For example, an out of home activity conflict would first be divided based on the planning horizon of the original activity. If the activity was planned within the same day (a value of 2 for APLAN), the percentage overlap is next evaluated. If the overlap percentage is less than 97%, the conflict would be resolved by modifying the original activity in 88% of cases, while if the overlap is over 97% the conflict is resolved by modifying the conflicting activity with an 86% probability. The attributes near the top of the table represent the most significant determining factors in selecting the appropriate strategy, as they affect the largest number of decisions. When a terminal node in the decision tree is reached, the resolution strategy is employed by choosing a strategy according to its probability at each node. The use of a probabilistic assignment at the leaf nodes allows the distributions from the modeled conflict resolutions to match more closely to the actual data.

TABLE XIX
DECISION TREE CONFLICT RESOLUTION MODEL RULES

Decision Rule Variables for Out-of-Home Activities																	
APLAN	1	2	2	3	3	3	3	3	3	3	3	3	4	4	999	999	999
OVERLAP	-	<97%	>97%	-	-	-	-	<50%	>50%	-	-	-	-	-	-	-	-
ADUR	-	-	-	<15	15-45	15-45	45-60	60-299	60-299	>299	>299	>299	-	-	-	-	-
CONTYPE	-	-	-	-	-	-	-	-	-	-	-	-	3,2	1,4	3	2,1	4
TAVAIL	-	-	-	-	<11	>11	-	-	-	<30	>30	-	-	-	-	-	-
B_LOC	-	-	-	-	-	-	-	-	-	0	0	1	-	-	-	-	-
Resolution Strategy																	
Mod. Orig.	38%	88%	5%	6%	4%	39%	38%	69%	13%	77%	16%	64%	61%	25%	68%	19%	0%
Mod. Conf.	30%	8%	86%	3%	8%	17%	19%	7%	13%	0%	0%	0%	4%	55%	0%	11%	58%
Mod. Both	14%	4%	5%	0%	0%	12%	14%	6%	3%	17%	2%	23%	26%	15%	23%	30%	15%
Delete. Orig	19%	0%	5%	91%	88%	32%	30%	18%	71%	7%	82%	13%	9%	5%	9%	41%	27%

Decision Rule Variables for In-Home Activities										
A_TRAVEL	0	1	1	1	1	1	1	1	1	1
B_TRAVEL	-	0	0	0	0	1	1	1	1	1
CONTYPE	-	1	2,4	3	3	-	-	-	-	-
SENIOR	-	-	-	0	1	-	-	-	-	-
A_PER	-	-	-	-	-	1	1	2,3	2,3	2,3
B_DUR						<170	>170	-	-	-
B_PLAN						-	-	3,999	1,2,4	1,2,4
OVERLAP	-	-	-	-	-	-	-	-	<98%	>98%
Resolution Strategy										
Mod. Orig.	0%	66%	81%	100%	86%	27%	57%	13%	50%	26%
Mod. Conf.	100%	0%	0%	0%	0%	4%	5%	50%	0%	19%
Mod. Both	0%	0%	0%	0%	0%	69%	14%	16%	30%	4%
Delete. Orig.	0%	34%	19%	0%	14%	0%	24%	22%	20%	52%

Note: Variable names are defined in TABLE XVII

After the decision tree model for activity conflict resolution was created, the discrete choice models of resolution strategy were evaluated for comparison purposes Within both the MNL and NL models, separate in-home and out-of home sub-models were estimated as was done for the decision tree model, in order to observe the differences in resolution strategies for in-home and out-of-home conflicts Each discrete choice model defines the utility for the four potential resolution strategies of modify the original activity, modify conflicting, modify both or delete the original The NL model was used since it was felt there were potential correlation issues between the various modification strategies, especially with the third strategy containing elements of both the first and second strategies Therefore, within the NL model the modification resolution strategies were grouped into one nest with an associated utility function, and the delete strategy was left as a degenerated nest having only one choice Due to this, the inclusive value parameter for the deletion nest was fixed to one for all NL models

The final parameter values and significance tests for each modeling type for both the in-home and out-of-home conflicts are shown in TABLE XX below As the table shows, the included variables and the actual parameter values tend to be similar in the MNL and NL models The only real difference between the model structures usually occurs when two or three of the modification utility functions include the same variable in the MNL model, the variable tends to move to the utility for the modification nest in the NL model Both the MNL and NL model seem to fit the data well, and the signs on the parameters tend to conform to expectations from the exploratory analysis and decision tree results The in-home models had adjusted R-squared values of 0 51 and 0 53 for the MNL and NL models respectively and the out-of-home models had values of 0 278 and 0 250, indicating good model fit

TABLE XX

CONFLICT RESOLUTION RESULTS FOR MNL AND NL MODELS

In-Home Conflict Resolution Model

	MNL		NL	
Variable	Coef	t-stat	Coef	t-stat
Const. and Inc. Vals.				
Modify Both. const.	-0.73	-1.25	-1.84	-2.44
Modify Inclusive Value	–	–	0.38	4.91
Delete Inclusive Value	–	–	1.00	Fixed
Original Activity Attr.				
ADUR (mod. orig.)	0.01	3.59	–	–
ADUR (mod. conf.)	0.01	3.72	–	–
ADUR (mod. both)	0.01	4.90	–	–
ADUR (mod. nest)	–	–	0.01	5.28
APER2 (mod. conf.)	3.90	3.90	5.06	4.00
APER3 (mod. conf.)	2.98	-3.50	4.00	4.52
APER3 (del. orig.)	1.23	3.78	0.83	2.78
APLAN2 (mod. orig.)	1.90	2.39	2.60	2.03
APLAN3 (mod. conf.)	-2.13	-3.50	-2.97	-3.67
APLAN3 (del. orig.)	-0.79	-2.39	-0.70	-2.49
APLAN4 (del. orig.)	-2.00	-2.36	-1.84	-2.32
ATIME (mod. orig.)	-0.77	-2.33	–	–
ATIME (del. orig.)	–	–	0.60	1.81
ATRAV (mod. orig.)	2.45	4.68	3.00	3.80
ATRAV (mod. conf.)	-6.64	-6.81	-7.86	-6.54
Conflicting Activity Attr				
BDUR (mod. conf.)	0.00	2.71	0.00	2.84
BPLAN3 (mod. conf.)	3.50	5.31	4.78	5.21
BPLAN999 (mod. conf.)	1.81	2.20	2.45	2.40
BTIME (mod. orig.)	-0.93	-2.57	-1.40	-2.74
BTRAV (mod. orig.)	-2.35	-8.69	-4.26	-6.64
Conflict Attributes				
OVERLAP (mod. orig.)	-2.50	-3.25	–	–
OVERLAP (mod. conf.)	–	–	1.96	2.60
OVERLAP (mod. both)	-2.40	-2.85	–	–
OVERLAP (del. orig.)	-1.49	-2.17	–	–
LL at zero	-600.1		-600.1	
LL at convergence	-288.5		-279.2	
Adjusted r2	0.512		0.529	

Out-of-Home Conflict Resolution Model

	MNL		NL	
Variable	Coef	t-stat	Coef	t-stat
Const. and Inc. Vals.				
Modify Orig. const.	2.15	6.25	2.40	8.69
Modify Conf. const.	-1.31	-3.39	0.52	1.26
Modify Both. const.	-0.10	-0.26	–	–
Delete const.	–	–	–	–
Modify Inclusive Value	–	–	0.80	5.44
Delete Inclusive Value	–	–	1.00	Fixed
Original Activity Attr.				
ACHILD (mod. orig.)	-0.70	-2.11	–	–
ACHILD (mod. conf.)	-1.20	-2.55	–	–
ACHILD (mod. nest)	–	–	-0.60	-2.10
ADUR (mod. nest)	–	–	0.00	2.32
ALOC (mod. conf.)	1.24	3.15	1.15	2.99
APER1 (mod. orig.)	0.83	3.15	0.81	2.92
APER1 (mod. both)	1.12	3.12	1.12	3.00
APLAN2 (mod. orig.)	1.12	1.97	–	–
APLAN2 (mod. conf.)	1.79	3.01	–	–
APLAN2 (mod. nest)	–	–	1.42	2.36
APLAN3 (del. orig.)	1.01	3.75	1.04	3.57
APLAN4 (mod. conf.)	1.42	2.99	1.22	2.65
APLAN999 (mod. orig.)	-1.40	-4.20	-1.52	-4.54
Conflicting Activity Attr				
BDUR (del. orig.)	–	–	0.00	2.36
BPLAN3 (mod. both)	1.17	3.53	1.24	3.82
Conflict Attributes				
CTYPE3 (mod. conf.)	-2.87	-2.78	-3.84	-3.77
CTYPE3 (del. orig.)	-0.73	-2.35	–	–
CTYPE4 (mod. orig.)	-0.81	-1.79	-1.64	-3.92
OVERLAP (mod. orig.)	-2.69	-6.28	–	–
OVERLAP (mod. both)	-2.70	-5.26	–	–
OVERLAP (mod. nest)	–	–	-1.48	-3.98
LL at zero	-627.2		-627.2	
LL at convergence	-447.4		-465.4	
Adjusted r2	0.278		0.25	

Note: Parentheses indicate utility function for parameter, where 'MOD. NEST.' Indicates the utility function for the 'Modify' nest in the NL model.

'–' indicates parameter was not significant in the model.

The performance of both models was evaluated by determining the percentage of correctly identified cases when the models from TABLE XIX and TABLE XX are applied to the data. For comparison purposes, both a deterministic (highest probability choice always selected) and probabilistic assignment of the final resolutions from the modeled probabilities are used to determine the expected percentage of correct predictions. The correct prediction percentages, or model recall, are shown in TABLE XXI for each resolution strategy for each model as well as for the null model where all strategies are assumed to be Type 1 for deterministic, or are selected with the observed distribution for probabilistic assignment (i.e. constants only model). Note that the classification results for the decision tree model are shown for both the training and test datasets, while no test data set was used for the logit models.

TABLE XXI
PREDICTIVE ABILITY OF CONFLICT RESOLUTION MODELS

	% Correctly Predicted - Deterministic				
	RS-1	**RS-2**	**RS-3**	**RS-4**	**Overall**
DT-Training	90.7%	76.6%	16.5%	58.6%	72.4%
DT-Test	85.5%	69.2%	23.3%	52.0%	68.1%
MNL	90.1%	70.9%	13.8%	62.5%	73.4%
NL	91.2%	69.8%	16.0%	56.5%	72.5%
Null Model	100.0%	0.0%	0.0%	0.0%	46.9%
	% Correctly Predicted - Probabilistic				
	RS-1	**RS-2**	**RS-3**	**RS-4**	**Overall**
DT-Training	69.4%	68.6%	28.4%	54.3%	61.2%
DT-Test	63.6%	68.0%	30.0%	48.0%	56.5%
MNL	72.1%	72.5%	28.5%	48.3%	62.6%
NL	72.4%	71.5%	26.1%	52.7%	63.5%
Null Model	21.7%	3.0%	1.0%	6.7%	32.5%

Note: Resolution Strategy Types 1, 2, 3 and 4 are as defined in Table 2.

The results in TABLE XXI show that the use of the decision tree conflict resolution model allows for 72.4% accuracy in classifying strategies, the MNL model classifies 73.4% of cases correctly and the NL model classifies 72.5% of cases correctly for deterministic assignment and 61.2%, 62.6% and 63.5% respectively for probabilistic. Therefore, it appears no significant differences exist in the predictive ability of the models. All of the models have a strong ability to correctly classify strategy types 1, 2 and 4, with the decision tree model predicting type 2 resolutions better and the MNL model predicting type 4 better. This is especially important, since the ability to predict the skipping or deletion of the original activity (type 4) and the modification of the conflicting activity is critical to allowing conflict resolution models to move beyond scheduling based on priority alone. Additionally, the results show that over-fitting of the decision tree model has not occurred in this case, since the percentage of correct predictions has decreased only by around 4% from the training to the test set. The models also show a sizeable increase in predictive ability compared to a null model. For both the decision tree model and the logit models there is an percentage point increase in predictive ability of approximately 25% over the null model for deterministic and over 30% for probabilistic, indicating strong model performance.

11.3.5 Analysis of Derived Conflict Resolution Models

Analyzing the rules derived from the scheduling process data shown in TABLE XIX leads to interesting results about conflict resolution behavior, which could be generally applicable across a variety of areas and populations. Overall, it is observed that demographic characteristics do not appear to be significant factors in how conflicts are resolved. In fact only a few lower level decisions for in-home conflicts are determined based on these characteristics. For out-of-home conflict resolution, only scheduling and activity characteristics determine the strategy employed. This is similar to results observed in the study by Roorda and Miller (2005b), where in attempting to create estimates of activity precedence, the sociodemographic characteristics were also found to be relatively unimportant. Further analysis of this phenomenon should be undertaken for different populations. The conflict resolution rules derived from the decision tree model are analyzed below for in-home and out-of-home conflicts separately and are compared to the MNL and NL model results.

Out-of-Home Conflict Resolutions

In the decision tree model, the most significant factor in determining resolutions to an out-of-home activity conflict appears to be the planning horizon of the original activity. The spontaneous, same-day planned and routine activities have a much lower probability of being skipped or deleted compared to the pre-planned activities, as expected, with the predominant response being modification of either the original or conflicting activity. This is reasonable as the preplanned activities have a longer time frame so there is more possibility for higher priority conflicting activities to be generated. The type of conflict and overlap percentage can also play a significant role in determining the resolution strategy. Type 3 conflicts and conflicts with low overlapping of the original activity are resolved more often by modifying both activities and Type 4 conflicts and conflicts with a higher overlap percentage are resolved by modifying the conflicting activity or deleting the original activity. Finally, an important consideration for pre-planned original activities is the duration of the activity with longer duration activities less likely to be deleted and more likely to be modified. This most likely reflects the difficulty of rescheduling a long duration activity and the higher priority of these activity types. Other factors such as the time available in the schedule when the conflict occurs and the location of the conflicting activity also impact the resolution strategies to a lesser extent.

Similar results are observed in the MNL and NL model as were found in the decision tree model. In both models only the planning horizon, conflict type, personal fixity, duration, presence of children and overlap are significant in the utility functions. Additionally, the effects these variables have are similar to those observed in the decision tree model. The planning horizon coefficients for same-day and routine planning types are positive in the modification utility functions while the coefficient for preplanned activities is positive in the deletion utility function for both MNL and NL, following the same pattern observed in the decision tree. Type 3 conflicts increase the likelihood of modifying the original activity, while Type 4 conflicts decrease it. Similarly, increasing the overlap decreases the chances of modifying the original activity while if the activity is performed alone it has a higher chance of being modified. The only significant difference between the decision tree and logit models appears to be the importance of the presence of children, which does not show up in the decision tree, and the low importance of the original activity duration which does not show up at all in the MNL model. In both logit models, the presence of children decreases the likelihood of modifying either of the activities, indicating that the timing of these activities is relatively inflexible.

In-Home Conflict Resolution

The most significant factor in determining resolutions to an in-home activity conflict in the decision tree model is the travel required to participate in the activity, with the activity attributes and socio-demographic characteristics playing a much less important role. One interesting feature of at-home activity conflicts is that the original activity is deleted in only 16% of cases, as compared to 34% for the other conflicts representing a higher priority or need and more scheduling flexibility associated with many at-home activities.

For all activities where no travel is required to reach the original activity, the conflicting activity is modified. This situation occurs when the original activity is preceded by another in-home activity and shows the high priority that individuals place on these types of activities. However, if the original activity is preceded by an out-of-home activity, the conflict is almost always resolved by modifying the original activity, especially if the conflicting activity is preceded by an in-home activity. This situation would only occur when the person has an out-of-home activity planned between two in-home activities and a new in-home activity is generated which overlaps both the out-of-home and in-home original activities. This behavior again shows the strong preference individuals have for in-home activities and displays a type of inertia resisting out-of-home trips. However, when both trips are preceded by travel the response is less clear, and is dependent mostly on the individuals involved with the original activity and the planning horizon and duration of the conflicting activity. This is reasonable since the situation where both activities are preceded by travel is basically substituting one in home activity for another, for example coming home from work and relaxing or socializing versus participating in housework, etc. If no one else is involved in the original activity, either both activities are modified if the conflicting activity is short, or the original activity is modified. If there are others involved in the original activity the planning horizon of the conflicting activity and overlap percentage determine the response type.

The discrete choice models for in-home activity conflicts display many of the same characteristics found in the decision tree model. In both models the travel required is generally a very significant factor affecting the resolution strategy, with the original activity travel coefficient having a very large negative value for modifying the conflicting activity, and a large positive value for modifying the original activity, while the conflicting activity travel coefficient has a large negative influence on modifying the original activity. Other significant factors from the MNL model that were not found in the decision tree model include the personal fixity of the original activity, with activities conducted with others having much lower flexibility, the time fixity of both activities, which decreases the ability to modify the original, and the durations of both activities, which generally indicates more modification likelihood for longer activities. Also, the planning horizon of both activities figures prominently in both discrete choice models although it is mostly a non-factor in the decision tree model. Interestingly, the conflict resolution response to the planning horizon is significantly different for in-home versus out-of-home conflicts with regards to preplanned activities, with preplanned activities in an out-of-home type conflict usually deleted while in-home activities are more often modified. This shows the more inflexible nature of out-of-home preplanned activities, which likely take the form of scheduled activities that cannot be changed. One other difference occurs between the logit and decision tree models with the conflict type, which was a fairly significant variable in the decision tree model but does not appear in either the MNL or NL model.

11.3.6 Conflict Resolution Model Observations

In the development of the final conflict resolution model for ADAPTS, several methods for modeling individuals decision making behavior regarding resolving activity scheduling conflicts were compared. The models were based on actual scheduling process data collected in the CHASE survey. Both models showed that resolution strategies are chosen primarily based on the location of the conflict and some basic activity and conflict attributes, such as the planning horizon, travel requirements and durations of the activities and the type of conflict and amount of overlap. The selected strategies seem to be largely independent of the socio-demographic profile of the involved individuals, as has been observed in other studies (Ruiz et al. 2005, Roorda and Miller 2005).

The results of the decision tree models in representing activity conflict resolution are very similar to the MNL model, with both models having very good predictive ability. However, the decision tree gives a relatively simple, easily interpretable model of conflict resolution behavior, which can be thought of as representing the rules followed in conflict resolution. In contrast, discrete choice models tend to be more complicated to interpret. Discrete choice models have the advantage of generally being more policy sensitive due to the ability to represent continuous variables without discretization and, since it is a statistical model, the ability to calculate elasticities and sensitivities to changes in policy variables. However, since many of the key variables in the model are non-continuous and are not generally thought of as being policy variables this may not be a consideration for choosing a model form.

The use of conflict resolution models estimated from actual scheduling process data has the potential to lead to more realistic microsimulation models of travel demand. These models offer a significant improvement over the basic rules used in current generation microsimulation models. However, future work still remains in creating a fully functional conflict resolution model for implementation. Extending the model to estimate additional modification strategies and attributes, as in Ruiz et al. (2005) and Ruiz and Timmermans (2006), would be beneficial. Additionally, work remains in implementing the model in a full-scale microsimulation to compare the generated schedules to validate the results. Along with validating the model results, the transferability of the model, using scheduling process data from other regions and populations also needs to be evaluated. Finally, other model forms beyond decision tree and discrete choice models could be tested. The conflict resolution rules are just a part of the overall activity scheduling process, which in general determine how an activity scheduling operation is undertaken given the selected resolution strategy. The details of the actual scheduling process undertaken to resolve schedule conflicts are discussed in the next section

11.4. Implementation of Conflict Resolution Rules in Activity Scheduling

The previous section described a new set of conflict resolution strategies derived from observed scheduling data. Theses conflict resolution rules were then implemented in the ADAPTS scheduler using a set of newly developed scheduling rules derived from the TASHA model (Miller and Roorda, 2003). This section discusses conflict resolution as it is currently handled within the TASHA scheduling system, demonstrates how the conflict resolution model described in the previous section was used to update the scheduling rules for use in ADAPTS, and illustrates the differences between each system. First, a brief overview of the scheduling rules used in TASHA is presented.

11.4.1 Existing Scheduling Conflict Resolution in TASHA

The TASHA model is a computational process model which generates, schedules, and executes activities at both the household and individual level. The model generates activities in nine categories (business work, primary work, secondary work, return home from work, school, joint and individual shopping and joint and individual other activities) and adds them to four individual level project agendas (work, school, shop, other) and two household level agendas (joint shop, joint other) as described in Miller and Roorda (2003), where a ‘project agenda’ refers to an initial scheduling construct which holds an organized, consistent list of related activities which are waiting to be scheduled. As each activity is generated the scheduling rules described below are utilized to determine if and how the activity is added. After all agendas are created, the person schedules are then created by taking activities from each agenda in order of priority (work > school > joint other > joint shop > individual other > individual shop) and adding them according to the scheduling rules. The end result is a consistent, feasible activity and travel schedule for each individual.

Conflict resolution in the TASHA system is currently done using a series of assumed scheduling rules. After an activity is generated, the scheduling rules attempt to fit it into the appropriate project agenda and these rules handle any conflicts which occur between the new activity and the activities already in the agenda. A similar process occurs during the construction of the actual schedule, when a slightly different set of rules is used to resolve conflicts with original activities already in the planned schedule (see Roorda et al. 2005 for details). Both sets of rules begin by first taking the activity to insert and comparing it to the current agenda or schedule to see if it is in conflict with another activity. If any of the conflict situations which are shown in the upper portion of Figure 19 below are found a series of rules is followed to determine if the agenda or schedule can be modified. These rules include shifting the lowest priority activity first, then moving the surrounding activities, then truncating the duration of the activity. How each of these scheduling steps is applied is a function of the types of the activities involved in the conflict and the space in the surrounding schedule. For example, as shown in the figure, the current implementation of TASHA allows insertion operations (Case 1) to only take place within a work or home activity, and no activities are allowed to entirely overlap an original activity. If these steps all fail, the new activity is not added to the schedule. More details about both the project agenda and person schedule insertion rules can be found in Miller and Roorda (2003) and Roorda et al (2005).

11.4.2 Development of New Scheduling Rules with the Conflict Resolution Model

The ADAPTS scheduler which includes the new conflict resolution model follows the same basic structure as TASHA. Activities are added to the activity schedule according to their planning horizons or scheduling order. As the activities enter the schedule, if a scheduling conflict arises the scheduling conflict rules are used to resolve the conflict. A new set of scheduling rules has been defined which are an updated version of the TASHA scheduling rules. There are two major differences between the TASHA and ADAPTS schedulers: the expansion of the allowable conflict cases, and the use of the conflict resolution model to determine how the conflicts are resolved.

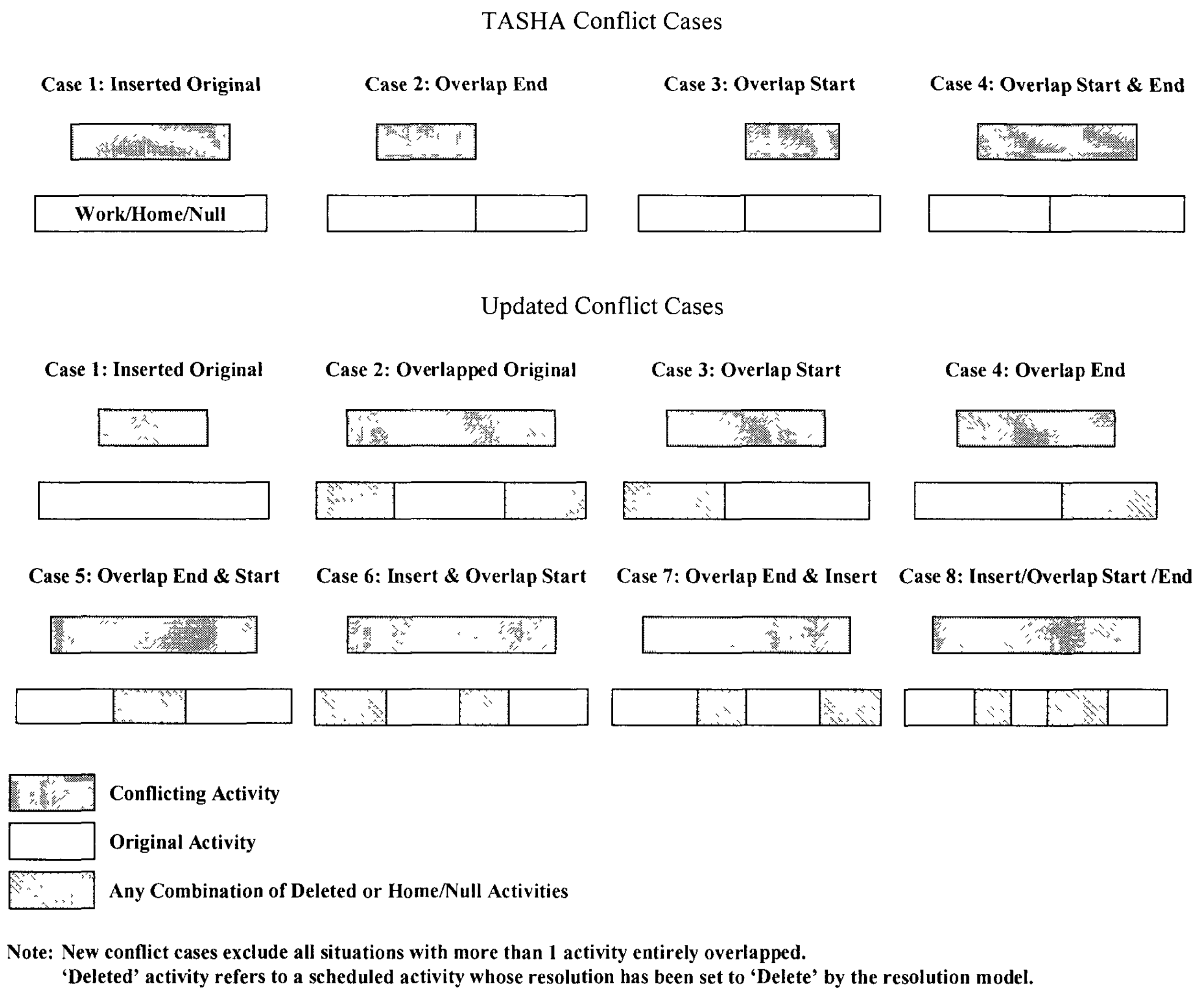


Figure 19. Conflict Types in TASHA and ADAPTS

The first change is the expansion of the allowable conflict cases. TASHA limits the conflict cases to those shown at the top of Figure 19. The two major limitations of the original rules are that activities can only be inserted into (and split) the work or home activities, and no original activity can be completely overlapped. Any conflict situation which did not conform to this was considered infeasible. These assumptions have been removed in the ADAPTS scheduling rules. Since the conflict resolution model and other empirical evaluations of process data have shown that different activity types can be split, the limitation to only splitting work and home activities was removed. And the most significant change is the addition of conflict cases which can completely overlap an original activity. In the analysis of the CHASE scheduling data by Roorda and Miller (2005), an activity is entirely overlapped in 23% of total conflict cases, and of these cases over 60% result in the original activity being deleted. Under the original TASHA rules, however, these cases would all be considered infeasible. Expanding the rules to account for these cases allows the scheduling process to more realistically represent actual scheduling.

The second major difference between the TASHA and ADAPTS scheduling process is the addition of the conflict resolution model to the scheduling rules. Each conflict situation shown in the bottom of Figure 19 represents the base conflict cases considered in the model, where each base case is composed of one or more component conflicts between an original and conflicting activity. When any activity is added to a schedule, it is first evaluated to see if there are any conflicts. If conflicts with any original activities are found, the conflict resolution model is used to determine the appropriate resolution type. If for any conflict the 'delete original' resolution is selected, the original activity involved in the conflict is provisionally deleted from the schedule. All remaining original activities in conflict with the conflicting activity are checked against the cases shown in Figure 19 to determine the base conflict case. After the base case is determined, there are additional sub-cases for cases which have insertion or complete overlaps which occurs near the start of the longer activity. In these cases the shorter activity is moved instead of splitting the longer activity as is normally done. For all of the cases there are further sub-cases which depend on the combination of resolution strategies for all of the component conflicts, i.e. which activities can be modified, and which are deleted. This leads to a total of 52 scenarios depending on the conflict case and resolution types as shown in TABLE XXII, each with a different set of scheduling rules. Any conflict case-resolution combination not listed in the table is considered infeasible.

For each combination of scenario represented by a conflict-case, sub-case and resolution type there are four final rules which are evaluated. For each scenario, the final scheduling rules are classified as:

- Insert the new activity with minimum shifting of modifiable activities
- Insert the new activity with no truncation
- Insert the new activity, truncate modifiable activities up to maximum
- Insertion is not feasible, delete the conflicting activity

TABLE XXII
SCHEDULING RULE CASES AND FEASIBLE RESOLUTION COMBINATIONS

CASE:	**Case 1**		
Sub Cases	Inserted near start of original	Inserted at end of original	Inserted in middle
Feasible Resolutions	Mod Orig, Con	Mod Orig, Con	Mod Orig, Con
	Mod Orig	Mod Orig	Mod Orig
	Mod Con	Mod Con	
CASE:	**Case 2**		
Sub Cases	Overlap at start of conflicting	Overlap at end of conflicting	Overlap in middle
Feasible Resolutions	Mod Orig, Con	Mod Orig, Con	Mod Orig, Con
	Mod Orig	Mod Orig	Mod Con
	Mod Con	Mod Con	
CASE:	**Case 3**	**Case 4**	**Case 5**
Sub Cases	(None)	(None)	(None)
Feasible Resolutions	Mod Orig, Con	Mod Orig, Con	Mod Orig1, Orig2
	Mod Orig	Mod Orig	Mod Orig1, Orig2, Con
	Mod Con	Mod Con	Mod Orig1, Con
			Mod Orig2, Con
			Mod Con
CASE:	**Case 6**		
Sub Cases	Overlap at start of conflicting	Overlap in middle	
Feasible Resolutions	Mod Orig1, Orig2	Mod Orig1, Orig2, Con	
	Mod Orig1, Orig2, Con	Mod Orig1, Con	
	Mod Orig1, Con	Mod Orig2, Con	
	Mod Orig2, Con	Mod Con	
	Mod Con		
CASE:	**Case 7**		**Case 8**
Sub Cases	Overlap in middle	Overlap at end of conflicting	(none)
Feasible Resolutions	Mod Orig1, Orig2, Con	Mod Orig1, Orig2	Mod Orig1, Con
	Mod Orig1, Con	Mod Orig1, Orig2, Con	Mod Orig2, Con
	Mod Orig2, Con	Mod Orig1, Con	Mod Orig3, Con
	Mod Con	Mod Orig2, Con	Mod Orig1, Orig2, Con
		Mod Con	Mod Orig1, Orig3, Con
			Mod Orig2, Orig3, Con
			Mod Orig1, Orig2, Orig3, Con

Note For each resolution case shown above, 'Mod' refers to the modification of the activities listed after the colon The activity labels are defined as follows Orig – originally scheduled activity, where Orig1, Orig2, Orig3 refer to the first, second and third (if any) originally scheduled activity if there are more than one, Con – conflicting activity

Inserting the activity with minimum shifting is done when there is enough space in the schedule such that less than the full number of modifiable conflicts are modified For example, if an edge conflict occurs between two activities and the resolution is such that both can be modified, if there is enough room in the schedule only one of the activities needs to be shifted depending on whether there is more room available before or after the conflicting activities in the schedule. Often times, however, there will not be enough room in part of the schedule to only shift the minimum number of activities and all of the activities will need to be moved, using up to all of the available space in the schedule to fit the activities If the maximal shifting of activities has been reached but the conflict still remains, the final strategy is to begin truncating all activities which have a resolution strategy allowing modification.

Finally, if all activities have been fully truncated and the conflict is still not resolved, the insertion is considered infeasible and the new activity is not added to the schedule. An important difference from TASHA here is that all modifiable activities are truncated in the final scheduling step rather than limiting truncation to the non-work, non-school activities alone.

Several restrictions on these rules are applied when implemented in the ADAPTS system. The maximum allowable shifting of activities within the schedule is controlled by the activity start time flexibility, with high flexibility activities allowed to move much further in time to resolve conflicts. The maximum time for each flexibility level is left as a model parameter, with values of 0.5, 2 and 4 hours as the current defaults. The maximum amount of truncation is also determined based on a flexibility parameter, in this case the duration flexibility. Highly flexible activities can be truncated more than low duration flexibility activities. Currently the maximum truncation percentages range from 50% for flexible activities down to 10% for low flexibility. Several restrictions also apply to the splitting of activities, with a minimum required initial duration activity having to be met before splitting can occur (currently 2 hours in ADAPTS). The split operation also can not result in an activity shorter than the minimum allowable duration (1 hour). Finally, once it is important to note that all of these restrictions apply to the initial duration of the activity and continue to apply to any activity spawned from an original activity through splitting. In other words, an activity cannot be truncated beyond the maximum amount no matter the number of truncation operations applied.

11.4.3 Comparison of Original TASHA versus ADAPTS Scheduling Rules

To demonstrate the differences that exist between the TASHA scheduling system and the ADAPTS scheduling rules, the full rules are presented for each system for one conflict type. The case shown is when a new non-business activity is added which overlaps the end of an at home or null activity and the start of another activity which is a non-home and non-null activity. This situation corresponds to a sub-case of the Case 4 type found in TASHA shown at the top of Figure 19 and the Case 3 situation as shown the bottom of Figure 19 for the ADAPTS rules. The limitation to a non-business conflicting activity applies only to the TASHA rules as conflict resolution in the new model is not dependent on the activity type.

In the TASHA rules, the activity would be resolved by checking each rule below sequentially, where Activity A refers to the new activity and Activity B to the overlapped activity (the home activity is overwritten as needed). If at each step the conflict is not resolved the next rule is checked until all rules have been examined. The rules are as follows:

i. Move Activity A, align end of Activity A with start of Activity B
ii. Move Activity B backward
iii. Truncate Activity A and Activity B proportionally to their durations
iv. Insertion is not feasible.

Under the new rules, the same situation would be handled as follows:

i. If resolution type is 'Delete Original'
   a. Remove Activity B from schedule, add Activity A
ii. If resolution type is 'Modify Original'
   a. Move Activity B, align start of Activity B with end of Activity A
   b. Truncate Activity B
   c. Insertion is not feasible
iii. If resolution type is 'Modify Conflicting'
   a. Move Activity A, align end of Activity A with start of Activity B
   b. Truncate Activity A
   c. Insertion is not feasible
iv. If resolution type is 'Modify Both'
   a. Move Activity A, align end of Activity A with start of Activity B
   b. Move Activity B backward
   c. Truncate Activity A and Activity B proportionally to their durations;
   d. Insertion is not feasible.

Note that 'Delete Original' activity is not listed in TABLE XXII and is in actuality not handled during the scheduling rule stage although it is shown above for clarity. This is due to the fact that all conflicts for which the original activity is deleted according to the conflict resolution model are resolved by removing the original activity from the schedule before the conflict case is determined. If at any point the insertion fails, all activities which were deleted prior to scheduling are reinserted into the schedule and the conflicting activity is dropped. For example, if a new activity is added which overlaps three activities, two of which are overlapped entirely and one which is overlapped only over its start, this would create three conflicts for this conflict case. As long as the conflicts between the new activity and the two overlapped activities were resolved by deletion, they would be provisionally deleted from the schedule and the conflict case would now be Case 3 as shown at the bottom of Figure 19. The rules above would then be implemented to resolve the remaining conflict. If the remaining conflict could not be resolved then the provisionally deleted original conflicts would re-enter the schedule. This allows the scheduling rules to handle situations where many activities are overlapped as long as most of them are deleted.

The use of the above scheduling rules gives an updated scheduling system derived from the TASHA model which can handle an increased number of conflict cases and resolves the conflicts in a manner more consistent with findings from scheduling process data. This allows the scheduling system to more closely mimic the process of activity scheduling, a s several of the assumptions have been replaced by rules that are based on scheduling observations. It is important to note, however, that although the conflict resolution model replaces some assumptions, many still remain, such as the order and magnitude in which activities are shifted, when activities are split, the direction which activities are moved and the amount by which they can be truncated. Therefore, a comparison of scheduling results is needed to ensure that replacing the original assumptions actually does provide benefit to the accuracy of the scheduling system. The next few sections describe how this comparison was made.

11.4.4 Activity Scheduler Comparison Using Chase Data

Several preparation steps were needed in order to utilize the CHASE data in the comparison. First, the data was filtered to remove low quality observations, which resulted in a final set of 260 individuals. Since the CHASE survey recorded all daily activities – including in-home activities such as sleeping, eating, etc. – the dataset was again filtered to remove all non-work in-home activities since TASHA does not consider the scheduling of these activities. The remaining activities were then reclassified using the disaggregate activity types into the nine TASHA activity categories. In order to use the CHASE survey to compare scheduling, two sets of activity data are needed; the originally planned schedule and the executed schedule. The planned activities are used as input to both schedulers, replacing the activity generation and planning stages, and the results are compared to the executed patterns. The planned activity data was generated by filtering the remaining data to extract all activity entries classified as 'modify' or 'delete', as these entries represent the results of a scheduling process. What remains is a list of all planned activities which includes the conflicting activities. To generate the executed schedules, a different filter was used to get the activities classified as 'executed' which represent activities which were in the actual travel pattern. These two activity data sets were then used to compare the TASHA and updated scheduling rules as detailed in the next section.

In this analysis the ability of both sets of scheduling rules to represent actual scheduling is evaluated. This is done by determining how closely each set of rules can replicated the observed activity patterns from the CHASE dataset when the initially planned activities from the dataset are scheduled. This analysis, therefore, replaces the activity generation and activity attribute planning stages of an activity based model with the known activities that had initially been planned in CHASE, where each activity generated already has a type, location, mode, planning horizon, etc. Unfortunately there are some potential issues with an analysis of this type, some of which can be overcome and some which remain in the final analysis.

Careful attention is required when determining what should and should not be a part of the initial schedule. In the previous data preparation section, the initial schedule was created by filtering for activities which coded as 'add' operations. The 'add' designation, however, can be misleading. For example, if the individual has scheduled a long duration activity and at some later time decides to insert a shorter activity into the original, the conflict will often be resolved in the survey by modifying the original activity to end at the start of the conflicting activity, and then adding a new 'add' activity after the conflicting activity. This is correct from the point of view of the user, but unfortunately leaves a second 'add' activity in the planned schedule. The second portion of the original activity is not a newly added activity, however, but the result of a scheduling process. Therefore it should not be included in the planned schedule otherwise it will in fact cause a conflict with the activity that spawned it, resulting in an extra conflict that should not be included. To correct for this conflicts between activities with identical attributes (other than start and end times) are not allowed and the conflicting activity is dropped.

Finally, for both schedulers, the activities are added to the agendas according to their planning horizons then according to the order in which they were planned in CHASE. This means that all of the routine or unknown planning horizon activities are added to the appropriate project agenda first in the order which they were scheduled, then the long-term preplanned activities, short-term activities, and finally impulsive activities For both schedulers, the activities are scheduled from the project agendas in the order as given in the TASHA model (Miller and Roorda 2003)

With these assumptions and limitations in mind, the CHASE activities were input to a newly created implementation of the TASHA scheduler and the ADAPTS scheduler The TASHA scheduler was run once and the ADAPTS scheduler was run 200 times, since the conflict resolution phase of the new scheduler, where the resolution types for each activity conflict are determined, is a stochastic process The results of each run were compared against the executed schedules through the use of a sequence alignment measure presented below

In order to compare the results of each scheduling system to the actual executed pattern, a time sequence alignment measure was calculated Much work has been done in the transportation and time use fields on sequence alignment (Joh 2004) For this analysis, a simple time difference measure is used over each activity-type pattern to determine how close the resulting schedule is to the executed one The difference measure is defined as shown below in Equation 22

This routine finds the cost for each individual by aligning the set of planned activities $\mathbf{A}^k$ to the executed activities $\mathbf{B}^k$ for each activity type k The total cost is defined as the sum of the weighted insertion, deletion and movement costs as given in Equation 22, where the component costs are defined in equations 23-25 The cost of insertion and deletion (C_D and C_I) *is* the sum of the durations (defined in Equation 28) of all deleted/inserted activities, with the set of deleted/inserted activities denoted by **D** and **I** in Equations 26 and 27 The cost of movement (C_M) is the cost to align the set of remaining activities in **A**, calculated by joining the set **I** to the complement of the set **D** in **A** (although one step of this operation is always trivial as either **D** or **I** will always necessarily be null), to its nearest counterpart in **B** as defined in Equation 31

To determine the set of deleted and inserted activities (**D** and **I**), the routine uses Equation 32 This equation defines the set **Z**, which for two sets **X** and **Y** is a subset of **X** if **X** contains more activities than **Y** or the null set otherwise The subset **Z** is defined such that its complement in **X**, is the same length as **Y** and the movement cost to align its complement in **X** plus the deletion cost to remove **Z** from **X** is minimized. The movement cost to align two sets with the same number of elements is given in Equation 31 which is simply the sum of the pair-wise difference between each element defined in Equation 29 (the difference between start and end times for each activity). So for the deletion case Equation 32 would be called with $\mathbf{A}^k$ and $\mathbf{B}^k$ in place of **X** and **Y**, respectively. The result of this equation is the subset of activities in **A** where the cost to delete those activities plus the cost to align the remaining activities to **B** is minimized. Note that this equation requires the checking of all possible combinations of activities to delete in **A** to find the minimization. The procedure to find the set of activities from **B** to insert in **A** is merely the reverse of the deletion procedure as implied by Equation 27.

$$C = \sum_{k=1}^{K} w_{D,I}(C_D^k + C_I^k) + w_M C_M^k \quad (22)$$

$$C_D^k = \sum_{i=1}^{\bar{f}(\mathbf{D})} f(\mathbf{D}_i) \quad (23)$$

$$C_I^k = \sum_{i=1}^{\bar{f}(\mathbf{I})} f(\mathbf{I}_i) \quad (24)$$

$$C_M^k = \bar{g}(\mathbf{A} \setminus \mathbf{D} \cup \mathbf{I}, \mathbf{B}) \quad (25)$$

$$\mathbf{D} = \bar{h}(\mathbf{A}^k, \mathbf{B}^k), \text{where } \mathbf{D} \text{ is the set of activities deleted from } \mathbf{A}^k \quad (26)$$

$$\mathbf{I} = \bar{h}(\mathbf{B}^k, \mathbf{A}^k), \text{where } \mathbf{I} \text{ is the set of activities inserted to } \mathbf{A}^k \quad (27)$$

where:

C = total alignment cost for an individual

$w_{D,I}, w_M$ = weights for deletion/insertion and movement operations

$\mathbf{A}^k$ = set of activities of type k to align

$\mathbf{B}^k$ = set of activities of type k that $\mathbf{A}^k$ is aligned against

$$f(x) = |end(x) - start(x)|, \text{ where } x \text{ is an activity} \quad (28)$$

$$g(x, y) = |(start(x) - start(y)) + (end(x) - end(y))|, \text{ where } x \text{ and } y \text{ are activities} \quad (29)$$

$$\bar{f}(\mathbf{X}) = \text{number of elements in } \mathbf{X}, \text{ where } \mathbf{X} \text{ is a set of activities} \quad (30)$$

$$\bar{g}(\mathbf{X}, \mathbf{Y}) = \sum_{i=1}^{\bar{f}(\mathbf{X})} g(\mathbf{X}_i, \mathbf{Y}_i), \text{ where } \mathbf{X}, \mathbf{Y} \text{ are sets of activities} \quad (31)$$

$$\bar{h}(\mathbf{X}, \mathbf{Y}) = \begin{cases} \mathbf{0}: & , \bar{f}(\mathbf{X}) > \bar{f}(\mathbf{Y}) \\ \mathbf{Z}: \mathbf{Z} \subset \mathbf{X} \wedge \bar{f}(\mathbf{X} \setminus \mathbf{Z}) = \bar{f}(\mathbf{Y}) \wedge \mathbf{Z} \text{ minimizes } w_m \bar{g}(\mathbf{X} \setminus \mathbf{Z}, \mathbf{Y}) + w_{D,I} \sum_{i=1}^{\bar{f}(\mathbf{Z})} f(\mathbf{Z}_i) & , \text{otherwise} \end{cases} \quad (32)$$

It should also be noted that this method is explicitly a one-dimensional alignment routine. The alignment algorithm only considers one attribute (activity-type in this case) when performing the alignment operations. The attribute could be expanded by combining activity type with the activity location, for example, but an activity with the same type as an activity in the actual schedule but a different location would be considered just as different as an activity with no similar attributes. Therefore the procedure can only meaningfully be used with one attribute measure. Fortunately this is not a significant issue because the planned and executed schedules tend to contain activities which only vary in the activity type attribute i.e. most scheduling conflicts occur between activities of different type, not activities of the same type with a different location, so only considering the type variable is a reasonable assumption. Under these assumptions, and with judicious choice of weighting factors, the algorithm can produce meaningful measures of schedule difference. The next section details the results of applying this algorithm to the TASHA and ADAPTS scheduling results.

11.4.5 Comparison Results

The schedule alignment routine outlined above was applied to both the results from using the TASHA scheduling rules and the results from 200 runs applying the ADAPTS rules. This analysis was done using a variety of weighting factors for the alignment operations as well. For each run, the movement cost was set to 0.5. This means for example an activity which had to have its start time and end time decreased by 10 minutes, would have a total movement cost of 10 minutes (10 minutes for moving both the start point and end point multiplied by the weighting factor). This weighting therefore says that movement costs are equal to the amount that the activity is shifted temporally to match the start times plus half of the additional lengthening or shortening to match the end times. The deletion/insertion weighting parameter was then tested at values of 1, 2 and 3, and the total scheduling alignment costs calculated as shown in Equation 22. The results of the analysis are shown in TABLE XXIII below.

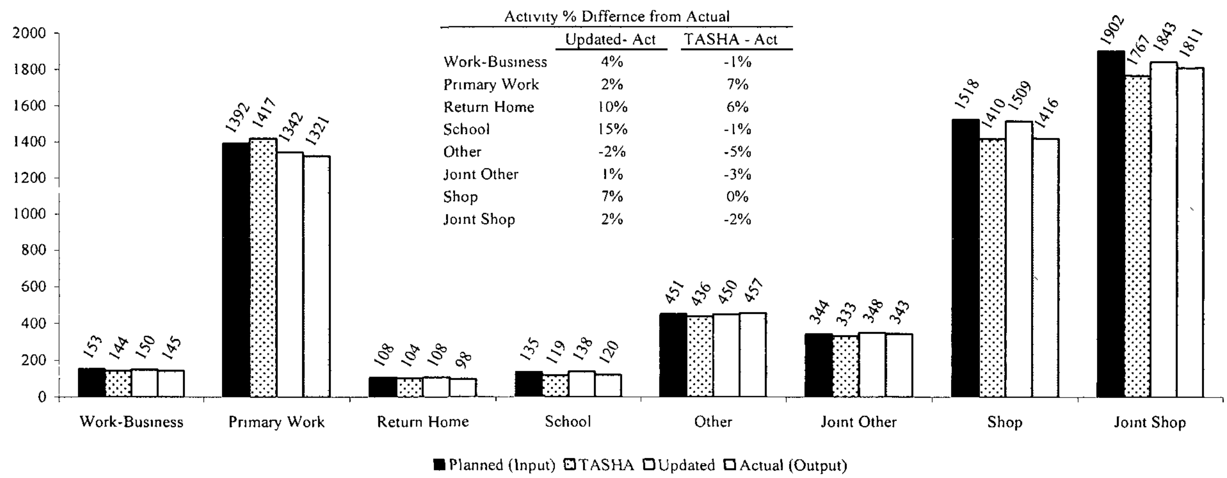
The results show that for all cases the new scheduling routine using the conflict resolution model has significantly better performance when compared to the original scheduling rules. When the insertion and deletion cost are weighted at 1 (2x the movement cost), the new model offers 17% improvement in fit over the original rules. This holds for all values of the weighting factor tested (up to 3 or 6x the movement cost) which represents a likely realistic range. Increasing the factor much beyond this favors a schedule which has closest to the total number of activities for each type found in the actual schedule, while not accounting enough for the amount that those activities need to be moved, while reducing the factor too much would not penalize enough a schedule which was too unrealistic in terms of the number of activities inserted and deleted. Therefore, for reasonable ranges of the weighting factors, the new scheduling results show marked improvement to the fit of the modeled schedules.

TABLE XXIII
SCHEDULING COMPARISON RESULTS FOR TASHA VS. ADAPTS

	$W_{Del,Ins}$	Delete Cost	Insert Cost	Move Cost	Total Cost
TASHA	1	352	212	3,115	3,680
ADAPTS - avg	1	349	371	2,336	3,055
ADAPTS - std	*1*	*16*	*23*	*230*	*225*
% change	–	–	–	–	*-17 0%*
TASHA	2	684	371	3,156	4,211
ADAPTS - avg	2	643	624	2,464	3,731
ADAPTS - std	*2*	*31*	*35*	*234*	*225*
% change	–	–	–	–	*-11 4%*
TASHA	3	995	532	3,199	4,726
ADAPTS - avg	3	931	902	2,563	4,396
ADAPTS - std	*3*	*38*	*56*	*176*	*159*
% change	–	–	–	–	*-7 0%*

Note TASHA refers to the scheduling results of a newly generated implementation of the TASHA scheduling rules
New scheduling model results averaged of 200 model runs
For all cases TASHA result is outside of 99% C.I. of updated model mean.
Run time was 3.4s for both simulations created in C#.NET and run on a 2.0GHz dual-core processor with 2GB of RAM.

Another estimate of how well the scheduling system is functioning is to evaluate some aggregate statistics. This is done by looking at the numbers of each type of activity scheduled and the average duration of those activities. Figure 20 shows the results of this type of analysis, which compares the total number and average duration of each activity type against the CHASE planned and executed patterns. The total activity count comparison shows that both scheduling systems produce approximately the same amount of each activity as found in the actual schedule, with the ADAPTS system performing better on work episodes and the TASHA rules on individual shopping activities. Similarly, the average durations for both models do not generally show any statistically significant difference. However, the average duration of the primary work episode from the TASHA scheduler was significantly different from that found in the actual schedule, while using the ADAPTS scheduling rules produced durations which all had no statistically significant difference from the actual results. For the remaining activity types, the ADAPTS model generally outperforms the TASHA rules except for school and work-business activities.



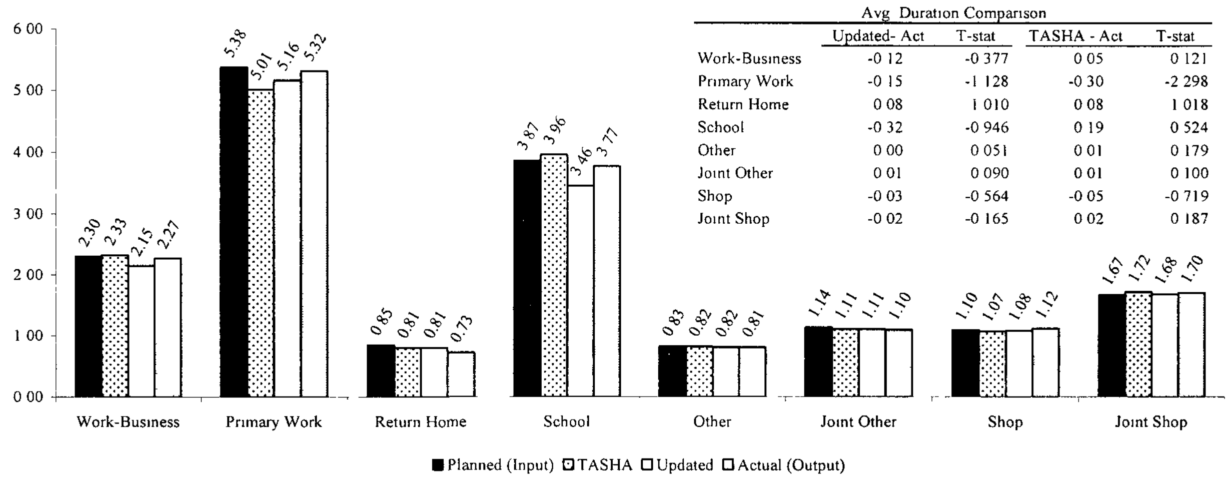


Figure 20. Count and Average Duration Comparisons

11.5. Application of Scheduling Rules in ADAPTS Framework

This chapter has detailed the development of an advanced set of activity scheduling rules based on the TASHA scheduling model for use in ADAPTS, and compared these rules against a new implementation of the original TASHA scheduling rules to measure their effectiveness. The updated rules feature the use of a new activity conflict resolution model which had previously been estimated to replace some of the assumed conflict resolution rules found in the TASHA rules. The use of new conflict resolution rules allows the updated scheduling rules to consider a wider range of conflict situations more closely resembling those found in activity scheduling process data, such as the CHASE database. Additionally, the updated rules allow the scheduling model to consider the removal of a previously scheduled activity which had not previously been implemented in any scheduling system with which the author is familiar. This was important, as conflict resolution of this type represented approximately 14% of all conflict resolution results found in the CHASE process data (Roorda and Miller 2005).

The accuracy of each model was estimated by scheduling planned activities found in the process data using each model and comparing the results to the actually executed activities. The accuracy was measured through the use of a simplified uni-dimensional time sequence alignment measure which calculates the amount and magnitude of scheduling insertion, deletion and movement operations required to conform a schedule to another given schedule. The updated rules were shown to significantly improve performance over a realistic range of weighting parameters used in the alignment procedure. The model showed a 17% improvement in fit over the TASHA rules when the magnitude of insertion and deletion weights was twice that of the movement weight. These results demonstrate that using models and rules based on data representing the actual underlying activity scheduling processes is feasible, with negligible impact on run-time and can result in real benefit to model accuracy and realism.

More work remains, however, in validating models of this type. As the conflict resolution model is developed using the same dataset which is used to test the model performance, it would be helpful to validate the results found here with additional scheduling process datasets. Additionally, the ability of the model to accurately represent scheduling for different regions and populations remains to be tested. Results showing that the underlying scheduling processes tend to be relatively homogenous across different individuals are encouraging (Roorda and Miller 2005, and Auld et al. 2008), but analyses which apply a model in different regions from which it was created are needed to investigate spatial transferability of these processes.

The conflict resolution and activity scheduling rules represent the final component of the ADAPTS model framework. The conflict resolution and activity scheduling rules are combined with the activity generation and activity planning modules to form a fully functional activity scheduling simulation model. The ADAPTS activity scheduling model can then be integrated with a dynamic traffic assignment and simulation model to form the final activity-based travel demand model, which is the subject of the following section.

12. TRAFFIC ASSIGNMENT AND SIMULATION

12.1. Traffic Assignment Background

The final stage in the completion of the ADAPTS simulation model was the implementation of a new traffic assignment and simulation routine. Traffic assignment is the process by which the demand generated in the activity planning and scheduling phase is realized on the transportation network for the modeled region. This involves converting the activity-travel plans to loads on the network, in order to evaluate expected real-world impacts from the forecasts being made and the policies being tested. Traffic assignment procedures generally result in measures such as vehicle miles travelled (VMT) and vehicle hours travelled (VHT) and speeds, travel times and delays encountered on network links. This process allows policies to be evaluated in terms of costs and benefits to travelers and represents the final output of a travel demand model.

Historically, travel demand models generally used in practice have implemented traffic assignment as the final step of the four-step model. After trips had been generated, distributed and split by mode, the resulting origin-destination trip matrices by mode would be assigned to a transportation network through some type of static equilibrium procedure, whereby the travelled paths between any origin and destination all had equal travel times. This was usually done with one trip matrix for the entire day and resulted in loads on the network in terms of volume per day on the links. This procedure may then have been followed by several feedback steps, whereby the demand was re-generated (rarely), redistributed, split into new mode shares and then reassigned as before. This could then be continued until some type of convergence was reached. Later improvements included using time-periods within the day and some time-of-day modeling in the trip generation step to assign trips at set time intervals.

Since ADAPTS was conceived as a fully integrated dynamic model, a new type of traffic simulation procedure was needed. Existing traffic simulation procedures were not found to allow for direct integration of the activity planning and scheduling phase of the simulation. The assignment routine for ADAPTS can be termed a time-incremental dynamic traffic assignment (DTA) using simulation. This is a DTA simulation where the process is stopped at each timestep to feed results back to the activity planner and scheduler. The key innovation here is that the current location, time and experienced link travel times are available at each planning stage to allow new planning or rescheduling to occur, depending on how well the experienced travel time matches the expected time. This is a key difference between this application of DTA and models where an entire day of travel demand is assigned.

Some other key differences exist between the traffic simulation procedure described here and the basic DTA procedure. According to Chiu et al (2010), a typical DTA solution algorithm contains three primary stages: *Network Loading*, *Path Set Updating*, and *Path Assignment Adjustment*. The network loading stage represents the simulation (or analytical solution) results for the realized traffic times based on the selected routes. In most current models this stage is handled through some type of micro- or meso-scopic network simulation (Chiu et al. 2010). In the ADAPTS assignment procedure, however, this step is handled through a macroscopic simulation using volume-delay functions based on the Bureau of Public Roads (BPR) functions, which is a simplification of the simulation process. The realized traffic times resulting from this step are then used in the next step, where the shortest paths between locations are determined.

In many DTA models, time-dependent shortest paths are determined for time-of-day bins throughout the day in the *Path-Set Updating* stage. This means that there are many shortest paths between locations depending on the start time, where the link travel times are based on the expected time when the link is reached (Chiu et al. 2010). The ADAPTS model does not use time-dependent shortest paths to do shortest path selection, but rather uses the current travel time on each link. This can be done, however, because the shortest paths in ADAPTS are updated every 15 minutes, so that although the shortest path may be selected based on outdated information for long trips (i.e. the link travel time would change by the time the trip reaches the link), the link travel times are never more than 15 minutes out of date. It should also be noted that the 15 minute time step is merely a system setting in the model and this can be reduced to further enhance the accuracy of the assignment.

The final step in a DTA model is the *Path Assignment Adjustment* or rerouting step. Based on the updated shortest paths, some percentage of the travelers select new routes, which causes the network conditions to approach closer to an equilibrium solution (Chiu et al. 2010). This is the last step in one iteration of a DTA, after which the first stage of *Network Loading* is undertaken with the new routes. Again, however, this is the primary difference with the ADAPTS assignment, which is a "one-shot" model (Peeta and Ziliaskopoulos, 2001). Instead of an iterative procedure assigning the overall demand, this three step process is followed for each traveler at each timestep, where a new shortest route is generated, assigned and simulated for each traveler. The rest of this section discusses in more detail the traffic simulation procedure implemented in the ADAPTS model.

12.2. Traffic Assignment and Simulation Procedure

The traffic assignment procedure begins when the activity planning and scheduling for each timestep has been completed. In the process of planning and scheduling activities, the ADAPTS model creates a vector of activities for which travel is scheduled to begin within the current timestep, as well as a vector of trips which are currently in progress from the last timestep and collects these into a new *trip vector*. The trip vector contains a *trip object,* which is the common object used to pass information between the activity scheduler and traffic simulator. The *trip object* includes the following information which is set by the scheduler and remains fixed:

- Traveller ID
- Origin
- Destination
- Start time of trip
- Travel mode

As well three variable fields which are updated by the traffic assignment procedure:

- Current location (initialized to Origin)
- Current time (initialized to Start time)
- Has arrived flag (initialized to false)

Trips newly generated by the activity planner will have the three variable fields initialized to the starting values, while trips which have previously been returned to the planner but were not completed will maintain the values from the previous iteration of the traffic simulator so that trip history is maintained. It is important to note here that the current status of the trip returned from the traffic assigner to the planner is used even if the trip has not been completed. This is done since the potential exists for diverting the trip to a newly generated impulsive activity, deleting the trip and heading somewhere else if the travel is taking too long, or in some way altering the trip if the expected and realized travel times are mismatched. This is procedure, then, represents a discretized implementation of en-route replanning handled at 15 minute time intervals.

The trip vector containing the trip objects is then sorted by start time and randomized by traveler ID, so that no pattern exists in the order in which individuals are simulated, and passed to the traffic assignment procedure. The traffic assignment procedure utilizes several key data structures in order to process the simulation step. The primary data structure is the *NETWORK* class, which stores the list of *NODES* and *LINKS*, with their associated capacities, volume delay functions, signalization information, connectivity, functional class, etc. The *NETWORK* class assembles the nodes and links into a connected graph with edge weights determined by the BPR volume-delay function and the current volume on the link. The other data structure is the *USED_LINKS* table, which maps traveler IDs to the links they were traveling on in the previous timestep. This is used to update the current link volumes as each trip progresses through the network during simulation. The traffic assignment procedure itself contains two primary methods, *Trip Routing* and *Trip Simulation*, which are implemented for each trip in the trip vector in turn, and are alternated with another routine *Trip Completion*, which removes trips that were finished in the previous timestep from the network. Each of these stages of the traffic simulation model is discussed in the following sections, followed by an illustrated example of the traffic routing and simulation procedure.

12.2.1 Trip Routing

Trip routing is the first stage of the traffic simulation model. In the trip routing stage of the model a trip is selected randomly from the trip vector for routing. The router then attempts to build the shortest travel path between the current location, or origin if the trip is newly begun, and the destination of the trip. The shortest path is based on current network conditions at the time of the routing, so it takes into account all trips which are currently on the links from trips simulated previously in the timestep and from trips not yet removed from the last time step. In this way routing is always done for every individual on the loaded network, i.e. there are no shortest path selections made on uncongested links (except for during the model start up period) as there would be in a static incremental assignment procedure.

In the trip router, the A* path finding procedure is used where the links are weighted using the appropriate volume delay function for its associated functional class. The A* procedure is a heuristic shortest path selection procedure, which uses both the current cost to reach each node plus the distance from the current node to the target node when selecting routes (Hart et al. 1968). The procedure is a modification of the Dijkstra algorithm which removes routes where the distance from the current node to the target node becomes too large, leading to a much more efficient solution as all nodes do not need to be processed to determine the shortest path. The Euclidean distance heuristic is used in the A* procedure, where the distance is then converted to travel time using a speed of 55 mph, to ensure that the heuristic is admissible, i.e. will not overestimate the cost (Hart et al. 1968). In the A* implementation used, the heuristic cost function is further modifiable on how to weight each component, i.e. the experienced cost up to the current node and the estimated cost from the current node to the target node (Pohl 1970), as:

$$f(a,c|b) = \omega g(a,b) + (1-\omega)h(b,c) \tag{33}$$

Where,

$f(a,c)$ = evaluation function from goal node a to target node c through b

$g(a,b)$ = path cost from node a to node b

$h(b,c)$ = estimated cost from node b to target c using distance heuristic

ω = balance factor between experienced and estimated cost, where $0 \leq \omega \leq 1$

The weight can be adjusted between 0, which is the "greedy" solution where the procedure finds a result the fastest but is usually sub-optimal (Pohl 1970) and 1, which replicates the Dijkstra algorithm and searches all nodes since the distance heuristic is not used. In the current implementation for ADAPTS, the ω value is set to 0.5 which weights the distance heuristic evenly with the experienced cost, producing optimal routes. The weighting can be reduced as necessary as the run-time for performing a separate A* shortest path procedure for each trip can be substantial. However, in testing different ω values, it was found that lowering ω much less than 0.3 tends to underestimate expressway traffic.

After the routing procedure is completed for a trip, the set of used links is returned to the main traffic simulation module. The used links are then used in the simulation procedure to get the experienced travel times along the shortest path as described next.

12.2.2 Trip Simulation

After the set of shortest path links is returned, the trip simulation procedure is undertaken The simulation determines the traveler's experience using the selected links and also updates the expected link travel times The trip simulation begins by first determining if the traveler was traveling in the previous timestep by checking the *USED_LINKS* table for an entry with the traveler ID If the individual was traveling in the previous timestep, then the traveler is removed from those links by decrementing the volume on each link in the list Next, the traveler is pushed along each link in the shortest route in order As the traveler is moved across the link, he is added to the current link volume for the link and the travel time for the link is added to the current trip travel time The *USED_LINKS* table is also updated to include any new links used from the current time period This continues until the current trip travel time would exceed the end of the timestep, at which point the individual is stopped The *trip object* from the *trip vector* associated with the traveler is then updated in terms of the current location, current end time and the completion flag and added to the *output trip vector* which is returned to the ADAPTS planner Note that the current time is less than the timestep end time unless the travel time after the last link perfectly aligns with the timestep end time, since travelers are moved from node to node and do not stop in mid-link as is done in more detailed traffic simulators Therefore, for example, if the simulation end time is 9 15AM, the current time may be something like 9 13 44, and it is this time that simulation begins from for this particular trip in the next iteration

The volume-delay functions used to determine experienced travel times, and for the routing stage as well, come from the CMAP regional travel demand model (CMAP 2010b) The volume delay functions used for various facility types are

VDF1 $$T_t = T_0\left(1 + 0\ 15\left(\frac{V_t}{C}\right)^4\right) + \left[6\left(\frac{V_t}{C}\right) - 0\ 39G + 0\ 35S - 4\ 5\right] + \left[2\ 7\left(\frac{V_t}{C}\right)^8 - 7\ 3\left(\frac{G}{S}\right) + 3\ 4\right] \tag{34}$$

VDF2 $$T_t = T_0\left(\mathrm{Min}\left(\frac{1+0\ 15\left(\frac{V_t}{C}\right)}{1\ 15}, 1\right)\right)\left(1 + 0\ 15\left(\frac{V_t}{C}\right)^8\right) \tag{35}$$

VDF3 $$T_t = T_0\left(1 + 0\ 15\left(\frac{V_t}{C}\right)^{10}\right) \tag{36}$$

VDF4 $$T_t = T_0\left(1 + 0\ 15\left(\frac{V_t}{C}\right)^4\right) \tag{37}$$

Where,

VDF1 = volume delay function for signalized arterials and exit ramps

VDF2 = volume delay function for freeways, expressways, tollways and freeway interchanges

VDF3 = volume delay function for metered freeway entrance ramps

VDF4 = volume delay function for all other links

T_t = link travel time (in seconds)

T_0 = free-flow link travel time (in seconds)

V_t = volume at time *t* on link

C = link capacity

G = length of green time at signalized intersection (in seconds)

S = length of signal cycle at signalized intersection (in seconds)

12.2.3 Trip Completion

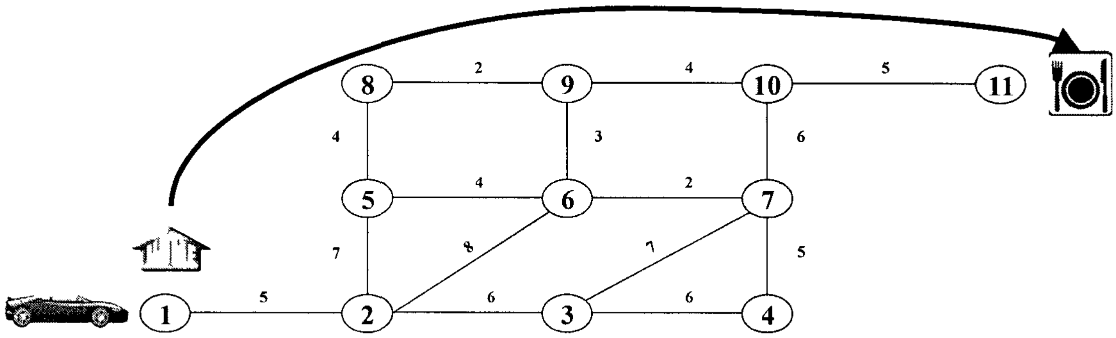
The final stage of the simulation is run after trip routing and trip simulation are completed for all trip objects in the trip vector. After trip simulation, the trip completion routine looks through the output trip vector for any trips which have been marked as completed. When such a trip is found, the routine cycles through each link in the trip and decrements the volume to simulate the trip leaving the network. Note that this is done after all trips have been assigned so that the impact of each completed trip is still felt on the network when all other trips in the timestep are assigned. After all of the completed trips are removed, the traffic assignment and simulation stage is completed. In the next section, a small example is presented for two timesteps of the trip assignment procedure for one trip in order to illustrate the assignment procedure.

12.2.4 Illustrated Example for Traffic Assignment

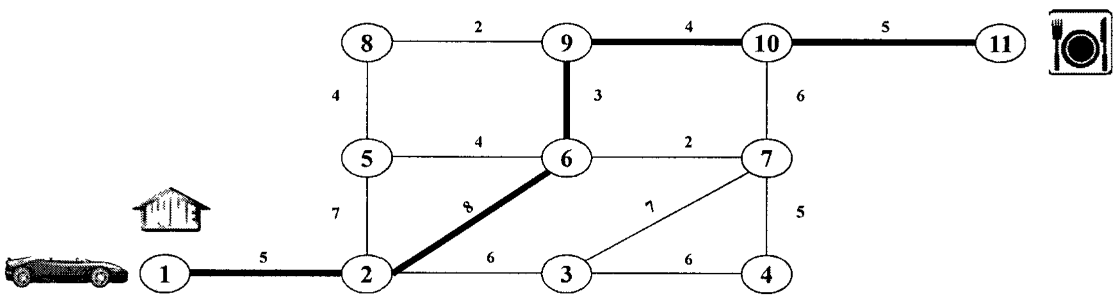
In this section, the traffic assignment procedure for one trip is demonstrated to illustrate the methodology behind the ADAPTS traffic assignment model. The assignment starts with a *trip object* added to the *trip vector* at timestep t. In the current example, we have a trip from an individual's home location to a nearby restaurant by car, and the trip is scheduled to begin one minute into the current timestep. The trip object at this time would contain the following information:

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	N1	N11	Auto	T+1	N1	T+1	False

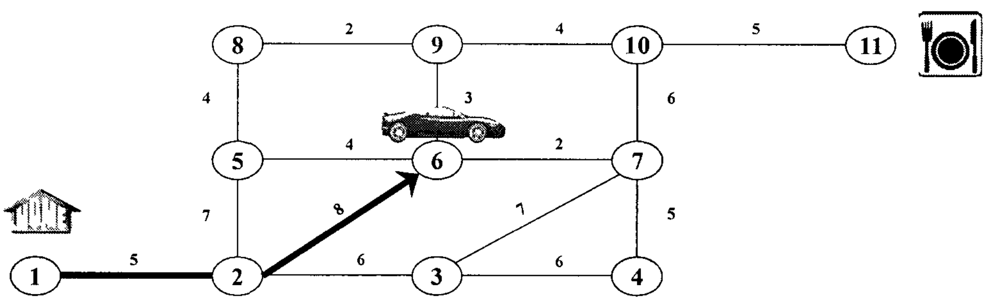
This trip is to be assigned to the network shown as in Figure 21(a). This information would then be sent to the router, which uses the A* algorithm to find the shortest path using the current travel times on each link calculated using the current volumes and the associated volume-delay function. The result of the shortest path calculation is shown in Figure 21(b), where the links *1-2*, *2-6*, *6-9*, *9-10* and *10-11* make up the current shortest path from node 1 to 11. The simulator then moves the vehicle along the shortest route one link at a time and increments the current time by the link travel time, so after traveling the first link, the current simulated time is T+6, and after the second link the time is T+14, after which no more nodes can be reached in the current timestep.



(a) Trip Vector Read in to Traffic Simulator from ADAPTS Timestep T



(b) Router Chooses A* Shortest Path Based on Current Network LOS: <1-2-6-9-10-11>



(c) Simulator Moves Vehicle Along Route Until End of Timestep
Update Link Volumes – Add to Links *1-2* and *2-6*
Report Trip Vector Back To ADAPTS

Figure 21. Network Simulation Example: Timestep T

Since the automobile is traveling on links *1-2* and *2-6* at this time, the volume from the trip is added to each of those links to represent the added congestion from the trip. The trip object is updated at this time and would now contain the following information, which is then returned to the activity planner:

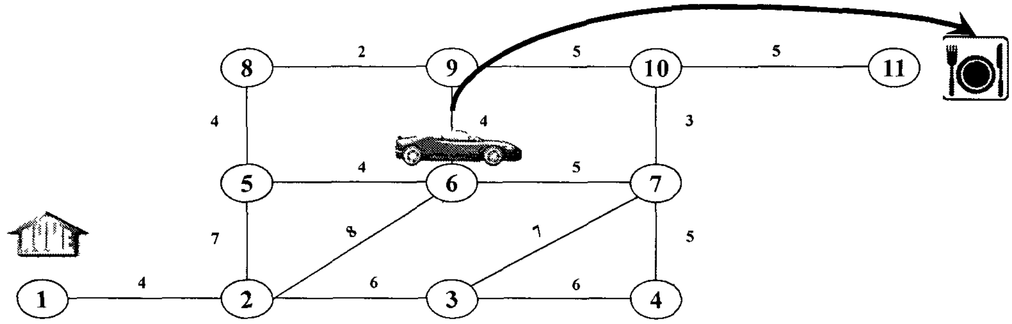
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Arrived?
1	N1	N11	Auto	T+1	N6	T+14	False

The activity planner would receive this information and notice that the individual was still traveling based on the *Arrived?* variable being set to false. This could lead to replanning of the trip, but in this case the trip is merely continued as originally scheduled. This means that the trip object written back to the traffic simulator contains the same information as above.

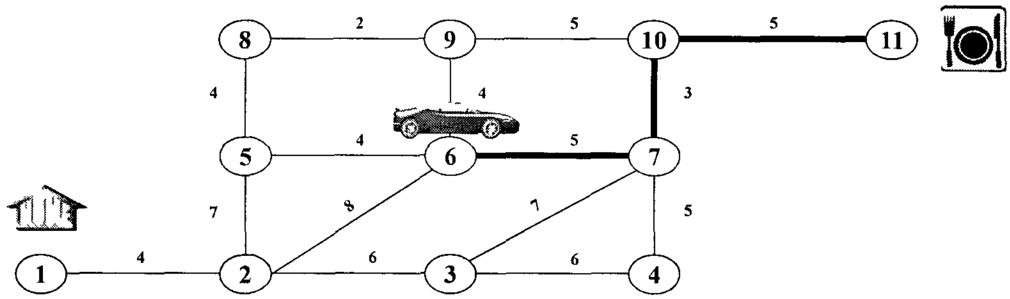
The process for assignment in the second timestep is shown in Figure 22. As in the first timestep, the simulation for this timestep begins by noting that there is a trip from node 6 to node 11 by car, which is in progress and is currently stopped at time T+14; one minute prior to the start of the current timestep at T+15. The trip is then sent to the router which calculates the shortest route based on the current travel times at T+15, updated for any trips which have come before the simulation of this trip. Note that the link travel times are not the same as in the previous timestep. The new shortest path now follows links *6-7, 7-10* and *10-11* as shown in Figure 22(b). Each link is traversed in turn and the current time is updated, with the time set to T+19 at node 7, T+22 at node 10 and T+27 at node 11, which is the destination of the trip. Since T+27 is less than the end of the timestep at T+30, the trip can be completed. The trip object is then updated as follows and sent back to the planner:

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	N1	N11	Auto	T+1	N11	T+27	True

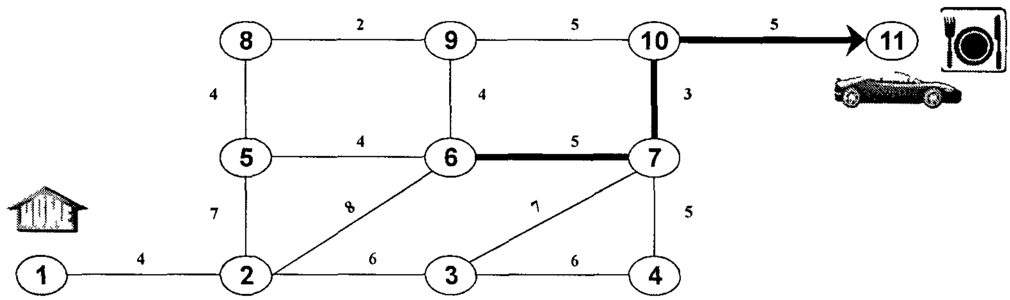
Notice that the realized travel time of 26 minutes is slightly longer than the expected travel time of 25 minutes from the first timestep. The planner now knows that the trip has been completed but has taken longer than expected, possibly causing rescheduling operations to occur. Also, because this trip was completed during the timestep, the added volume on links *6-7, 7-10* and *10-11* from this trip is removed after all other trips are simulated



(a) Trip Vector Read in to Traffic Simulator from ADAPTS Timestep T+15



(b) Router Chooses A* Shortest Path Based on Current Network LOS – Different Path From Time T



(a) Simulator Moves Vehicle Along Route Until End of Timestep (Or Destination Reached)
(b) Update Link Volumes – Add to Link *6-7*, *7-10* and *10-11*; Remove from Link *1-2* and *2-6*
(c) Report Trip Vector Back To ADAPTS

Figure 22. Network Simulation Example: Timestep T+15

The traffic assignment procedure documented above necessarily departs from the standard criteria for an equilibrium solution, namely that the solution is guaranteed to exist and that either path or link flows are unique. It has been argued, however, that the "ability to adequately capture traffic dynamics and driver behavioral tendencies precludes the guarantee of the standard mathematical properties" of the equilibrium solution seen in the static traffic assignment problem (Peeta and Ziliaskopoulos, 2001).

As demonstrated in this example, although time-dependent shortest paths are not used directly in the procedure, the timestep-based process produces approximate time-dependent shortest paths. The time-dependent shortest paths are approximate because although the shortest path is followed at each time step, there is a history dependence where choices in previous timesteps constrain the current shortest path to potentially sub-optimal time dependent paths (i.e. the traveler cannot start trips over once they have begun). Again, however, the accuracy of this approximation can be improved by decreasing the timestep size. Overall, however, the current procedure works well for simulating network conditions. The performance of the network simulation, however, is necessarily linked to the performance of the model as a whole. The demonstration and validation of the assignment procedure will be discussed further in Chapter 14, which discusses the overall model validation.

13. SIMULATION ENVIRONMENT

13.1. ADAPTS Model System Programs

The preceding chapters have focused on the development of the model framework and the individual components which comprise the ADAPTS modeling system. After the framework was developed and the various models were estimated, they were all implemented as an object-oriented set of software routines which collectively make up the ADAPTS activity-based model system. The model system itself is made of a suite of programs developed in the C#.net programming language and developed for Windows 64-bit operating systems. The programs include:

- PopSyn-WIN 5.0: used to generate the synthetic populations
- ADAPTS_v3: main activity-based model program
- AdaptsVIS: allocates trip episodes to network GIS files for visualization
- AdaptsResults: Used to read and process the ADAPTS output files

Screenshots of each of the programs can be seen in Figure 23 through Figure 26, respectively. Each program will be discussed briefly in this section, while the remainder of the chapter will focus exclusively on the development of ADAPTS_v3.

The first executable program developed, and the first used in the running of any ADAPTS model, is the PopSyn-WIN program shown in Figure 23. This program implements the population synthesis routines discussed in Chapter 7. The program allows the user to specify the input data files containing the marginal variables for the geography of interest as well as sample files of both person and household characteristics. The linkages between the files are then defined through the use of control variables, where the sample values are linked to marginal categories for the households and individuals. The program is left completely flexible in terms of the input and output data used, as long as the conditions listed in Chapter 7 are satisfied. After the data is defined, various settings can be applied to determine the generation characteristics, including marginal tolerances, stopping criteria and scale factors which all influence the run time and accuracy of the analysis. The settings options also allow the user to directly link the data to the required ADAPTS inputs so that the output synthetic population is ready to use in the ADAPTS model. Finally, the program contains a GIS interface which allows an analyst to develop forecast scenarios through the modification of marginal distributions for selected regions

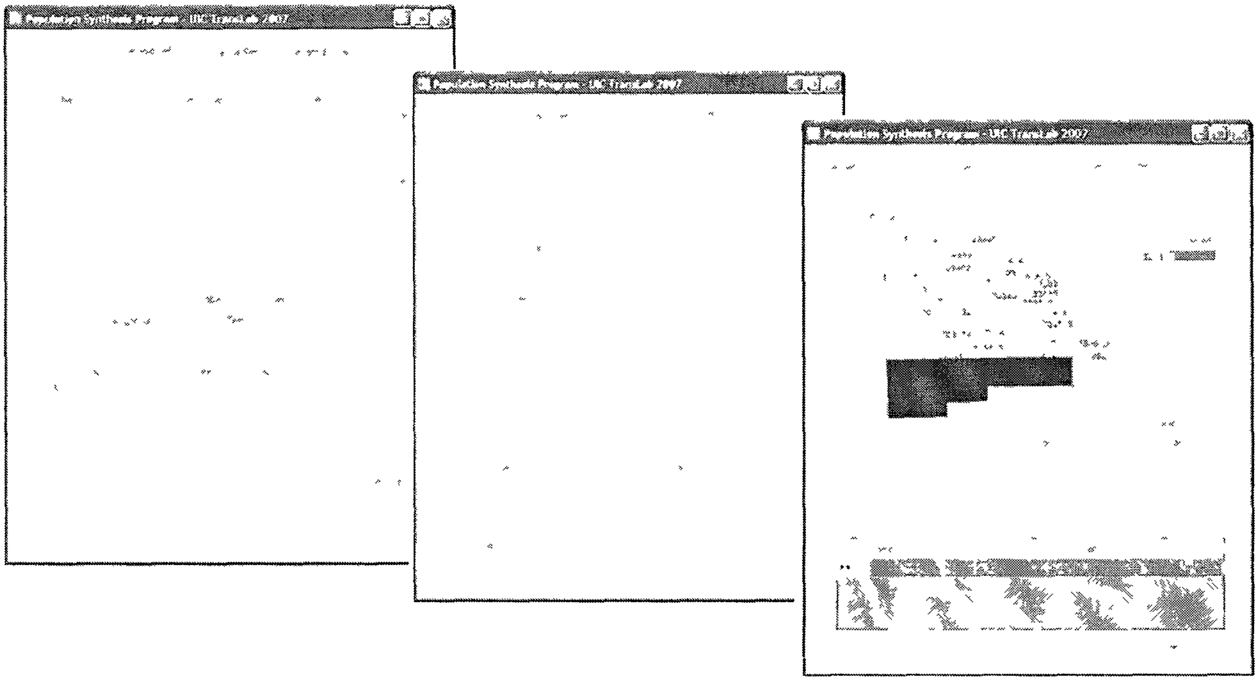


Figure 23. Screenshots of Population Synthesizer

The next program in the ADAPTS system is the ADAPTS_v3 simulation model itself. This program has a graphical user interface (GUI) which allows the user to specify the input files which contain the household, person, vehicle, zone and network characteristic, as well as specifying input files which define the activity generation, start time and destination choice model parameters. The program also allows various system settings to be defined, primarily dealing with multithreading through the use of a number-of-sub-problems and number-of-processors setting. Once the ADAPTS model is started through the GUI, the program console window is displayed, showing the current state of the model as it runs It includes output messages for every file read and all processing steps which are long-running. During the activity preplanning stage, it outputs a progress message every 20 seconds, and during the actual simulation stage a message is displayed after each timestep is completed, allowing the progress of the model to be tracked in great detail. The development of the ADAPTS_v3 program is discussed in the next section.

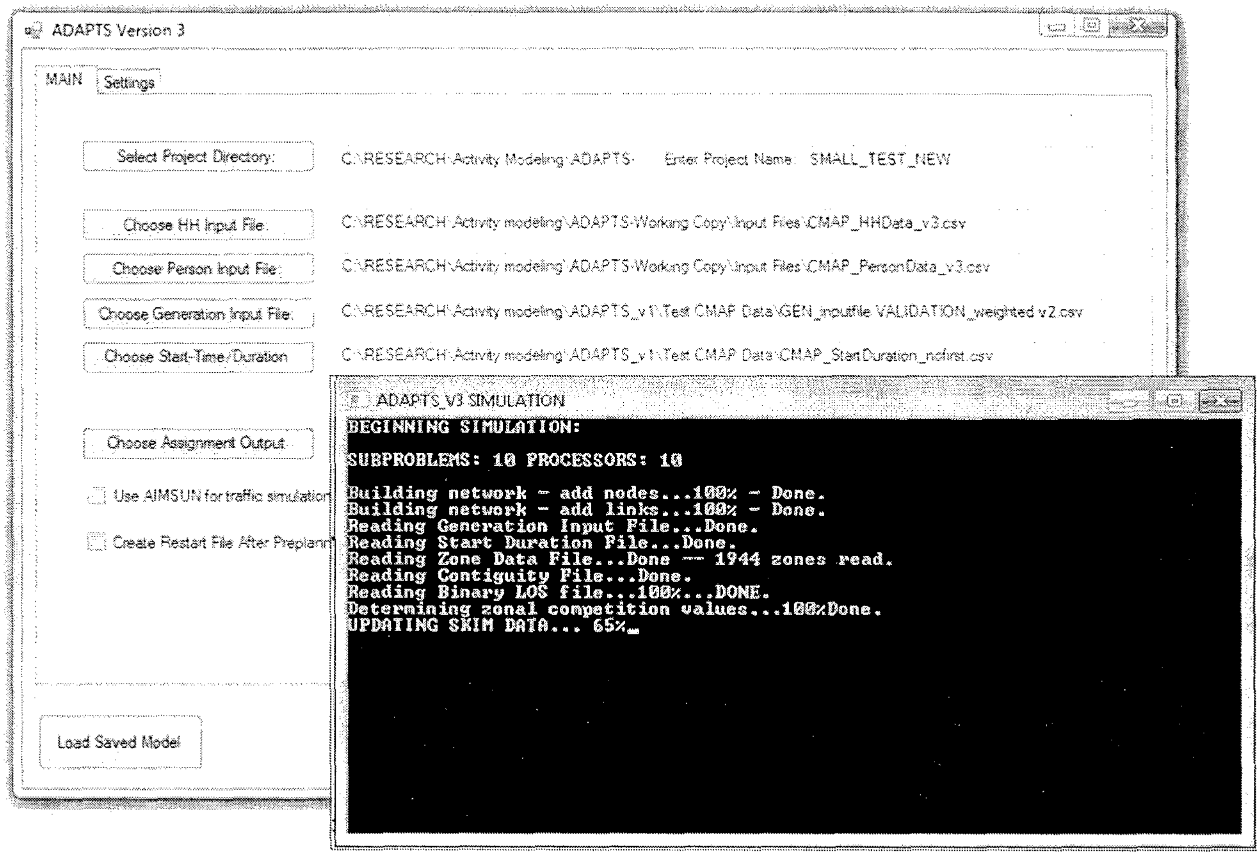


Figure 24. ADAPTS Main Program Window With Output Console

First, however, the two final programs in the ADAPTS system are the AdaptsVIS and AdaptsResults executables. These programs are both used to interpret the ADAPTS model results. This is especially important since for any sizable simulation run the output results are far too large to open in any commonly available text-editors or spreadsheet programs. However, the results require extensive aggregation and modification in order to be interpretable by a user. Therefore the AdaptsVIS program shown in Figure 25 and AdaptsResults program shown in Figure 26 were developed. AdaptsVIS uses the MapWinGIS open source GIS library to link the trip results to the network shapefile. The results can then be displayed in terms of link volumes, delays, travel times, etc. The data can also be displayed for all time periods for any individual link by clicking on it in the GUI. The program also contains aggregation features to report results by functional class, county, time of day, and other categories. Finally, the AdaptsResults program aggregates the activity and trip file results into distributions such as activity counts, average durations, average trip and tour lengths, start times, and many others.

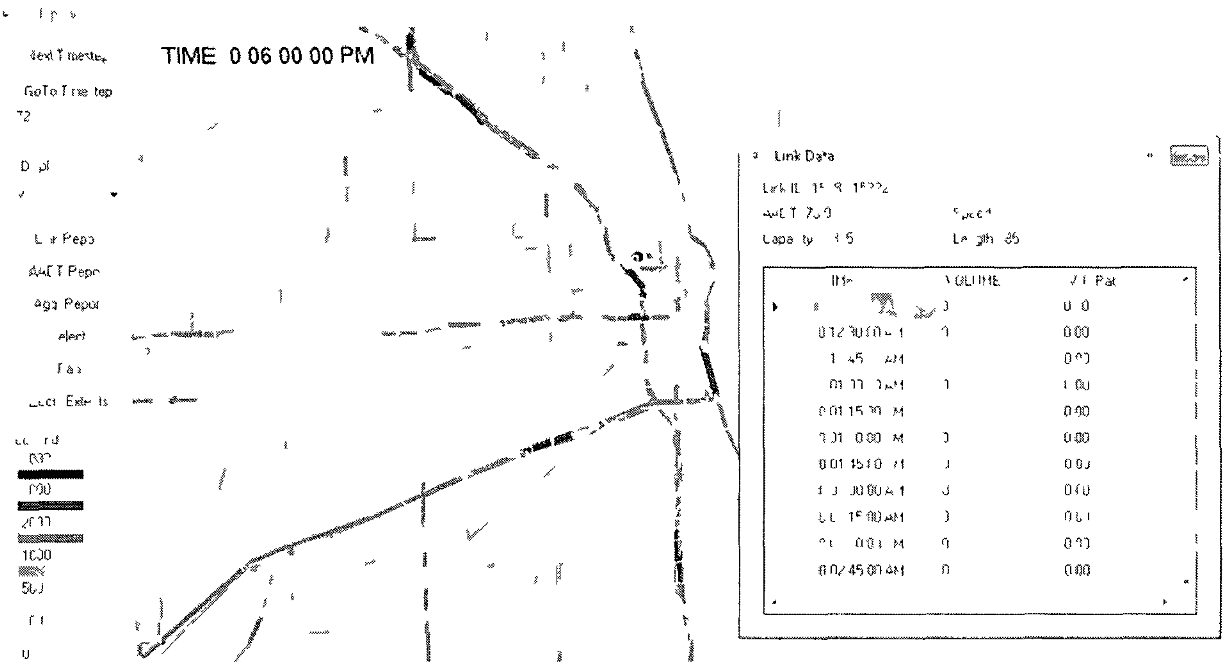


Figure 25. Screenshot of AdaptsVIS

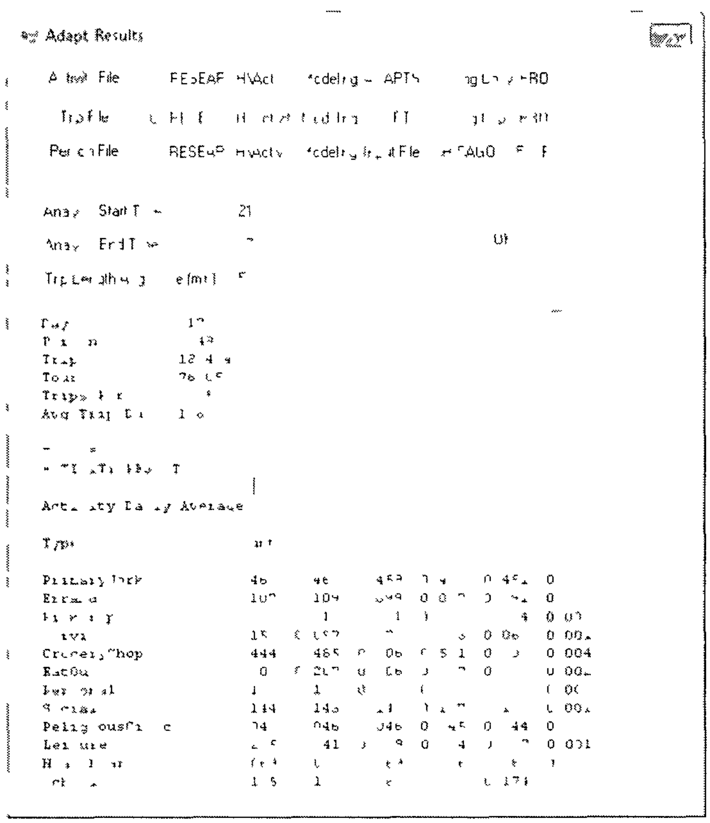


Figure 26. Screenshot of AdaptsResults

13.2. ADAPTS Simulation Environment

The simulation routines discussed in Chapters 8 through 12 were all implemented in an integrated object oriented simulation environment written in the C#.net programming language. The simulation environment consists of a large number of classes representing the various elements and agents in the simulation. The classes are instantiated in a Windows Form that has various file reading methods for each class and several controls for specifying project settings. The class objects are then created when the analysis is run from the form. Each object contains both data members describing the object and methods which govern how the object behaves and interacts with the rest of the environment. Also in the ADAPTS simulation environment are a number of static classes which act upon the objects as needed, and which implement many of the previously discussed model components. An overview of the classes developed for ADAPTS and how they interact is shown in Figure 27. Each class is detailed in the following sections.

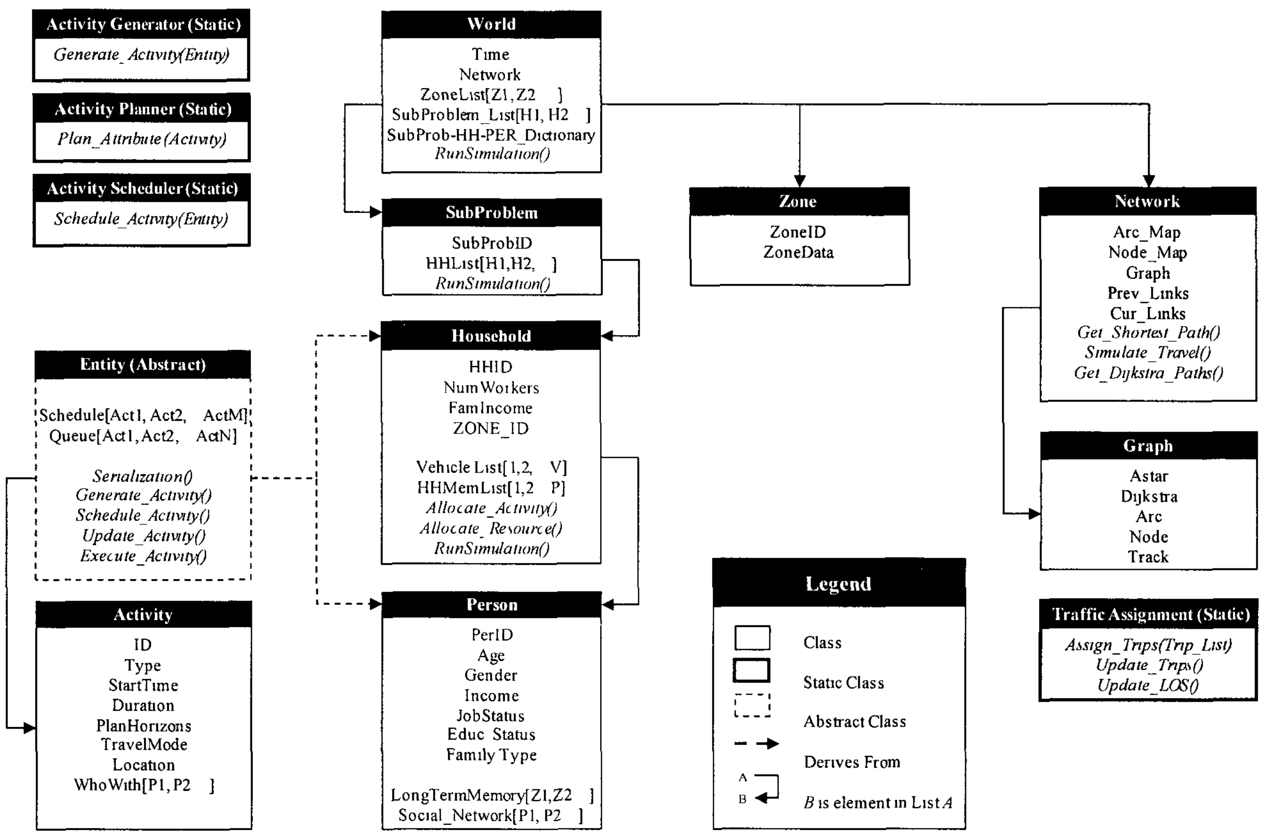


Figure 27. C# Simulation Environment Objects Diagram

13.2.1 *World*, *Subproblem*, *Zone* and *Network* Classes

The *World* class is the highest level object in the ADAPTS simulation environment This class represents the environment in which the simulation takes place, and as such contains lower level objects representing the physical environment, such as the analysis zones and the transportation network The *World* class also contains the simulation time and is the object in which the individual timesteps are processed The *World* class also contains many methods for accessing these objects and related data from other classes Examples of these methods include get functions for TAZ data and network level of service used in many of the activity planning models The *World* class also handles the threaded operations through the use of the *Subproblem* class list The *Subproblem* class is simply a container holding randomly selected households for processing When the number of threads to be used in the system is specified, the *World* class creates a *Subproblem* for each thread and adds the households from the household input file randomly into one of the *Subproblem* objects The simulation and serialization for each *Subproblem* can be handled separately enabling threaded processing In order to enable communication across threads between households, the *World* class also contains a *household-to-subproblem* dictionary, which gives the *Subproblem* address for each household in the simulation

The most important method in the *World* class is the *RunSimulation* method This function starts the different activity simulation stages and calls various simulation routines in the *SubProblem* class objects These include the *RunRoutineSimulation* method which does routine activity planning for work, work-related and school activities The method generates one week worth of these routine activities for each household in each subproblem and then copies the weekly schedule to the *Analysis Period* which is determined through program settings The default analysis period is one week In this stage the activities are merely added to the schedule, so that there is no simulation of the activity execution and travel in this stage Following the *RunRoutineSimulation* the *RunSimulation* method calls the *RunPreplanSimulation* routine which prepopulates the person activity schedules with preplanned activities This is handled in much the same way as the routine simulation, with no alternating between individuals within the same subproblem So a complete set of preplanned activities is generated for an agent and the simulation then progresses to the next individual and so on, until all agents have been preplanned This simulation stage is done merely to "warm-up" the final *Analysis Period* with preplanned activities, if the analysis period was started without the preplanning stage the preplanned activities would be underrepresented substantially in the final schedule

The final stage of the *RunSimulation* handles the main activity-travel simulation The routine starts at the first timestep in the analysis period and creates a new thread for each *SubProblem* It then calls the *RunSimulation* method of each *SubProblem* item and joins the execution threads on completion This represents one timestep of the activity planning phase After all the *SubProblem* threads are joined, the *World* class then calls the *AssignTrips* method of the *TrafficAssignment* static class, which will be discussed later The *World* class also handles all file outputs and writes the following for later analysis

- Activity File — a record of all activity details for activities completed during the analysis
- Trip Record File — a record of the trip details connecting each activity
- Routine Activity File — listing of all the routine (work, school) activities generated
- Link Count File — the network results file for use in AdaptsVIS
- Project File — Log of files used, errors encountered, run time, etc

In the same way that the simulation routine in the *World* class calls related simulation routines in the *SubProblem* class for each thread, the *SubProblem* routines call another set of simulation routines residing in the *Household* class This is done for each *Household* object in the *SubProblem Household_List* item The simulation routines residing in the *Household* class are described in the next section

Three other significant classes are important members of the *World* class and are accessed through it in the ADAPTS simulation model These include the *Zone*, *Network* and *LOS_Database* classes which reside in the *World* class The *Zone* class contains data on the traffic analysis zones used in the model, including land-use areas, employment by category, socio-demographic characteristics and others Individual *Zone* objects for each TAZ reside in the *Zone_List* collection of the *World* class The *Network* class also resides in the *World* class and consists of collections of *Arc* and *Node* objects as well as a single *Graph* object which connects the arcs and nodes into a network The *Arc and Node* objects contain the data required for the network simulation This includes coordinates, ID, cycle length and ZoneID for the *Node* objects, while the links contain ID, start and end nodes, capacity, length, lane, speed, facility type and green ratio information The *Graph* object has one public method, *Astar*, which handles the shortest path finding given start and end nodes The network object has several public methods, including the *GetShortestPath* method which calls *Astar*, and the *Update_Volume* method used to change the link volumes for traffic simulation Finally, the *World* class contains the *LOS_Database* class and allows public access to it using the *Get_LOS* method This database gives zone-to-zone travel times and is updated from the *Network* class through the *Update_LOS* routine, which is called at predefined intervals

A simplified, pseudocode representation of the *World* class *RunSimulation* process is shown in Figure 28, which also details some of the methods called in each step for the *SubProblem* and *Household* objects The majority of the simulation process is handled within the individual entity classes, which are discussed next

13.2.2 Entity Classes: Entity, Person and Household

The *Entity* classes represent the agents in the ADAPTS simulation The *Entity* classes are all derived from an abstract *Entity* base class which implements common functionality for all of the agents The *Entity* class contains two core data members, the *Schedule* which is a collection of time sorted *Activity* classes (detailed in section 13 2 3), and the *Planning_Queue* which is similar to the schedule but instead of time sorted planned activities, contains unplanned activity episodes and their associated planning flags, as discussed in Chapter 6 This means that all agents in the model, including household, persons, and eventually vehicles, have an associated schedule

The *Entity* class also implements many routines to handle additions to and modifications of the *Schedule* and *Queue* All of the scheduling rules presented in Chapter 11 and the conflict resolution model on which they depend are located in the *Entity* base class These rules determine how the *Schedule* for any agent is modified depending on the conflict type, activities involved and schedule characteristics The *Entity* class also has routines for determining schedule characteristics, i e time availability and activity rates, for ensuring the validity of the schedule, and for tracking the assigned thread of the entity, which is important for many operations

The simplest class derived from the *Entity* base class is the *Person* class This class does not contain many additional members beyond the base class It does contain a *PersonData* member, which is a subordinate class containing all of the socioeconomic data of the person The *Person* class also implements serialization members for simulations which are too large to hold in memory

```
// -----------------------------------------------------------------------------------------------------------------------
// ReadInput.ReadZoneFile()
// ReadInput.ReadPerFile()
// . . .
// WorldClass.InitializeNetwork()
// WorldClass.World.RunSimulation()
//     '-----------------------------------------------------------------------------------------------------------------
//     ' Routine Simulation '
//     '  this forms the routine portion of the individuals schedule, done all at once for each individual
//     '  one week of actual scheduling, copied to all remaining weeks of simulation (currently set to 4 weeks)
//     '-----------------------------------------------------------------------------------------------------------------
//     FOREACH WorldClass.SubProblem in World.SubProblemList[]
//          WorldlClass.SubProblem.RunRoutineSimulation()
//             FOREACH EntityClass.Household in SubProblem.HouseholdList[]
//                EntityClass.Household.RunRoutineSimulation()
//                   ... <see EntityClass.Household.RunSimulation below>...
//     '-----------------------------------------------------------------------------------------------------------------
//     ' Preplanning Simulation '
//     '  this generates the preplanned activities for the final 1 week of actual scheduling
//     '  i.e. actual scheduling is done during this stage, and only activities set to occur in final week are saved
//     '-----------------------------------------------------------------------------------------------------------------
//     FOREACH WorldClass.SubProblem in World.SubProblemList[]
//          WorldlClass.SubProblem.RunPreSimulation()
//             FOREACH EntityClass.Household in SubProblem.HouseholdList[]
//                EntityClass.Household.RunPreSimulation()
//                   ... <see EntityClass.Household.RunSimulation below>...
//     '-----------------------------------------------------------------------------------------------------------------
//     ' Actual Simulation '
//     '  this does the actual daily activity generation, planning and scheduling, including of the preplanned activities
//     '  from the last step, with full interaction with traffic simulation.
//     '-----------------------------------------------------------------------------------------------------------------
//     FOREACH Timestep:
//        WorldClass.ReadAssignmentResults()
//        FOREACH WorldClass.SubProblem in World.SubProblemList[]
//           WorldlClass.SubProblem.RunSimulation()
//              FOREACH EntityClass.Household in SubProblem.HouseholdList[]
//                 EntityClass.Household.RunSimulation()
//                    FOREACH EntityClass.Person in Household.MemberList[]
//                       ActivityGenerator.GenerateActivity(),
//                       ActivityPlanner.DestinationChoice(),
//                       ActivityPlanner.ModeChoice(),
//                       ...
//                       EntityClass.AddActivity()
//                          EntityClass.FindConflict()
//                          EntityClass.ConflictResolution()
//                          EntityClass.ImplementStrategy
//                       TrafficAssignment.AddTripIn()
//                    NEXT Person
//              NEXT Household
//        NEXT SubProblem
//        TrafficAssignment.AssignTrips()
//     NEXT Timestep
// END SIMULATION
```

Figure 28. ADAPTS Simulation Pseudocode

The other derived *Entity* class currently implemented in ADAPTS is the *Household* class, where most of the simulation routines reside Similar to the *Person* class, the *Household* class contains a *Household* data member class with demographic information as well as serialization methods The *Household* class also contains additional data structures which hold the *Persons* and *Vehicle* objects residing in the household A number of methods used to access the *Persons* and *Vehicles* in the *Household* are also included, allowing for the selection of unoccupied members, children, available vehicles, persons by relation and many other characteristics Along with these access methods, there are routines for adding household-level activities to individual members

The primary methods used in the household class are the *RunRoutineSimulation RunPreSimulation* and *RunSimulation* methods which are called by the similarly named *SubProblem* methods for each household in each execution thread An overview of how the simulation methods operate is shown in Figure 28 in the *foreach* loops over the households At each timestep the simulation methods loop through each household member and perform the activity scheduling routines as described in the overview of the ADAPTS framework in Chapter 6 and shown in Figure 3 The planning procedures are mostly handled in separate static classes which are called by the *Household* class simulation methods The static classes implement the models described in the preceding chapters of this thesis Each core planning component has its own static class The *ActivityGenerator* class takes an individual or household as input and returns generation probabilities The other static class is the *ActivityPlanner*, which includes methods for choosing start times, durations, modes and destinations The *ActivityPlanner* methods take an activity, individual and household as input and make probabilistic attribute decisions using the models described above Activity scheduling, as mentioned above, is handled in the *Entity* base class from which *Household* is derived

13.2.3 <u>Activity Class</u>

The *Activity* class represents the fundamental unit of analysis in ADAPTS The *Activity* class objects populate the household and individual schedules and drive the travel demand in the model *Activity* class objects contain many public methods and properties, and also contain a set of planning functions which are called by the *ActivityGenerator* class Some of the significant *Activity* properties relate to the primary attributes, such as the start and end time, a list of involved person IDs, and the location, travel mode and activity type These properties are all accessed through public methods

The *Activity* class also contains the plan horizon and flexibility information regarding each attribute and the planning flags for the attribute For example, for the travel mode, there is a *PlanHorizonMode* variable which determines the discrete plan horizon value and a *Flexibility_Mode* variable which represents the mode flexibility, both of which are set from the *Planning Order Model* discussed in Chapter 9 In addition there is a *WhenPlannedMode* variable which represents the mode planning flag and is a fixed point in the schedule at which the mode is to be planned, derived from the *PlanHorizonMode* variable The same pattern exists for the remaining attributes

The *Activity* class has two methods which set these variables and are called by the *ActivityGenerator* static class upon generation The first is *SetInitialActivityAttributes*, which implements the *Planning Order Model* and the second is the *SetActivityPlanTimes* method which uses the plan horizons and flexibilities to set the planning flags at specific times in the schedule The flags are set by choosing random time points within feasible ranges defined by the various plan horizons The process for setting the planning flag for an attribute is as follows

1 First, choose probable day from activity plan horizon range, for all but same day and impulsive activities, i e Same Week plan horizon -> between 2 and 7 days from time of generation
2 Weight possible days by the amount of free time and select randomly
3 Get random preplanning day from range defined by attribute plan horizon, i e if preplanned over one week, choose from 7 to 30 days prior
4 Set planning flag at random time on a preplanning day – if preplan day is prior to activity generation time, set plan flag at activity generation time

13.2.4 <u>Traffic Assignment Static Class</u>

The *TrafficAssignment* static class implements the assignment routine described in detail in Chapter 12 This class utilizes two primary methods which are called from the *WorldClass RunSimulation* method These are the *AddTripIn* method, which passes the trip objects into the *TrafficAssignment Trips_In* collection every time a trip is to start, and the *AssignTrips* method which is called after the planning stage is completed for each timestep The *AssignTrips* method then calls the *AssignTripsThread* method for each processing thread, which interacts with the *WorldClass Network* object as previously described The *AssignTripsThread* method assigns a set of trips for each thread from the *Trips_In* collection where the number of trips passed into each thread is determined by the *NumSerial* program setting This is currently defaulted to 20 trips The threads are joined after each thread finishes the *AssignTripsThread* method and the network volumes are updated This means that the *NumSerial* value multiplied by the *NumProcessors* value approximately indicates the increment size for the dynamic incremental loading procedure used If the *NumSerial* setting is lowered towards a value of one, the accuracy of the assignment procedure is increased, but significant processing is introduced through generating more threads and having a higher proportion of thread wait time due to the thread join after each iteration Finally, after all of the *TripObjects* in the *Trips_In* collection have been assigned and the completed trips removed, the updated trip results are returned to the *World* class for use in the next activity planning iteration

13.3. <u>System Settings Used in ADAPTS Simulator</u>

There are many configurable system settings that control how the simulation is performed in the ADAPTS simulation environment Most settings are stored in the *GlobalSettings* class, which is a static class available to all other classes The global settings generally pertain to the timing, scheduling and processing variables needed by many different classes Descriptions of the most critical settings and the functions they serve in the analysis are discussed next

One group of settings relates to the processing characteristics of the program through the *NUMSUBPROBLEMS* and *NUMPROCESSORS* settings These settings are used to divide the households into randomly assigned subproblems as determined by *NUMSUBPROBLEMS*, and assign the subproblems to a number of threads determined by *NUMPROCESSORS* The *NUMPROCESSORS* setting should not be set higher than the processors physically available in the machine on which the simulation is run, as this gives no performance benefit but does incur more thread overhead The simulation behaves differently depending on the relationship between the settings If *NUMSUBPROBLEMS* is less than the *NUMPROCESSORS*, the number of threads is reduced to the number of subproblems If *NUMSUBPROBLEMS* is greater than *NUMPROCESSORS*, serialization is used between each timestep for each subproblem Note that this significantly reduces the runtime of the analysis due to the need to read from disk instead of memory and should only be used when needed This option, however, is needed for either very large simulations or machines with limited memory A general rule-of-thumb observed in ADAPTS is that every 100,000 agents require about 2GB of memory So for example if an 800,000 agent simulation is run on a machine with 4 processors and 4GB of memory, the optimal parameters to set would be 16 subproblems and 4 threads This would divide the 800,000 agents into groups of 50,000, and would process four groups at a time using slightly under 4GB of system memory This analysis would require serialization between timesteps, as there are more subproblems than threads However, if an attempt was made to run the program without serialization (i e *NUMSUBPROBLEM=4, NUMPROCESSORS=4*), the system would run out of memory since 16GB is required

Another group of system settings are the timing variables, which determine when the simulation and presimulation start and stop, the timestep length and the time tolerance used in many of the routines The *simulation_start* time is the time (in days) at which the presimulation begins, while the *presimulation_end* time is the point in the simulation when presimulation ends and the full activity simulation begins Finally, the *simulation_end* time is the point at which the full simulation is completed During the presimulation and simulation phases the world time is advanced each timestep by an amount defined by the *time_increment* variable The default values used are 0 0, 21 0 and 28 0 days for the *simulation_start presimulation_end* and *simulation_end* variables respectively, and 15 minutes for the *time_increment* variable

A final group of system settings are used to control the activity planning and scheduling processes The *Min_Duration* value determines the minimum amount of time, excluding travel time, for which an activity can be scheduled The default value is 15 minutes The *Min_Split_Result Duration* is the minimum required duration of an activity which results from splitting an existing activity during a scheduling conflict This variable is included to ensure scheduling realism becasue individuals are unlikely to engage in an activity for a very short time before or after a split as it represents an inefficient scheduling resolution The current value is set to 60 minutes The *Min_Home_Duration* is also included to ensure scheduling realism This setting gives the minimum duration of a return home activity between two other activity episodes If the timing between the activity episodes is such that the individual could travel home, stay home for *Min_Home_Duration* then travel to the following activity, the individual will then return home Otherwise, rescheduling occurs with either the following activity moved up in time or the current activity being extended The default setting for this variable is 15 minutes plus the minimum of the inbound or outbound leg travel time for the return home activity Another important setting is the *Minimum_Truncation_Ratio* which determines how much an activity can be shortened as a result of a schedule modification operation. This variable is set to 50% for flexible activities by default, with the less flexible activities having a higher value. Finally, the *Min_Overlap* setting determines how much activities need to overlap before the overlap is considered a conflict. Any overlap less than the *Min_Overlap* value is simply split proportionally between the conflicting activities with no conflict resolution process. This value is 5 minutes by default.

13.4. Computational Environment and System Requirements

The ADAPTS model system is installed on an HP desktop computer with an Intel i7 hexacore processor which utilizes 12 processing threads. The system has 24GB of memory available for use. The ADAPTS system requires a 64-bit Windows operating system and the Microsoft.NET framework version 3.5. In order to run the simulation models of Chicago described in the next Chapter, 10 processing threads were used with a 10% sample of the region – about 790,000 agents. In order to run the entire simulation in memory, about 14GB of memory were needed. The run time for these simulations was approximately 11 hours per simulated day, or about 80 hours of run-time for one week of simulation, including the generation of routine and preplanned activities. More details about the simulation for the Chicago region are given in Chapter 14.

14. ADAPTS CHICAGO BASELINE MODEL VALIDATION

The ADAPTS activity-based model framework presented in this thesis was implemented for the Chicago region in order to validate the model as a whole and to determine how well the model functions as a regional travel-demand model. The model was implemented using the simulation software described in Chapter 13. Since the individual components of the ADAPTS model were mostly developed using Chicago regional data, the parameter estimates and heuristic rules presented in Chapters 8 through 12 are used directly without alteration, except for the activity generation model as will be discussed below. The model was run using a 10% sample synthetic population generated using the population synthesizer described in Chapter 7 and using the same control variables as previously described. The rest of this Chapter focuses on the implementation details for the baseline model and the validation results obtained from the model for comparison to existing household travel survey data, traffic volumes and results from the regional travel demand model.

14.1. Baseline Model Implementation Details

The baseline model was implemented for the six-county region surrounding the City of Chicago in Illinois. This includes Cook, DuPage, Kane, Lake, McHenry and Will counties. The regional transportation network was extracted from the CMAP travel demand model and includes all expressway, freeway and tollway links, most arterial links and centroid connector links meant to represent local streets. The analysis area is shown in Figure 29.

The population used in the analysis was generated using the population synthesis routine described in Chapter 7. The inputs to the synthesis routine were taken from the 2000 Census data summary files and the 2000 Public Use Microdata 5% sample, which generates the baseline year 2000 population. This population contained a total of 7,755,490 individuals living in 2,910,510 households. This population was then scaled linearly to represent the population growth in the Chicago region between the year 2000 and the 2007 baseline model year of approximately 600,000 individuals. After the Census 2010 estimates are released, an updated baseline 2010 population with more realistic household and individual distributions will be generated. A 10% sample of this final population was then extracted and used to run in the ADAPTS model. This introduces some simulation error, but is necessary at this point to obtain reasonable model run times.

An additional feature in the Chicago implementation was the inclusion of external and truck traffic on top of the regional passenger traffic. At this time, the external and truck trips are extracted from the CMAP regional model with the origins and destination fixed and the start times distributed using diurnal curves provided by CMAP (CMAP 2010b). This adds approximately 2.8 million additional daily trips to the transportation system which need to be accounted for in order to properly evaluate the model. These trips include 4 classes of truck trips, external trips bound for the regional airports, external pass through trips and external to internal trips (CMAP 2010b). In the future, it is expected that the truck trips can be derived from an activity-based freight model and directly integrate with the ADAPTS model system as shown in Figure 1.

The zoning system in the region is also taken from the CMAP travel demand model, and contains a total of 1,944 internal traffic analysis zones covering 20 counties, and 21 external zones for the external trips. The zones are then overlaid with the CMAP Land-Use Data (CMAP 2010a) and employment estimates to generate the zonal characteristics needed for the workplace and destination choice models. One limitation is that the land use data and employment data only cover the 6-county Chicago region, which is why the ADAPTS model only focuses on those counties. The estimated zone data contains information on employment in six job categories (retail, service, government, industrial, manufacturing and other) and land usage areas in many categories, such as retail, recreational, etc. Additional information on the socio-demographics of the zones was derived from Census data.

The ADAPTS model system was applied to this region with all of the models as described in the previous sections, with the exception of the activity-generation model. Because this model was estimated using the UTRACS data, it was not expected to be representative of Chicago as a whole. Therefore a calibration procedure was undertaken, whereby the scale factors of the individual activities were shifted until simulated model average activity rates matched those observed in the CMAP Travel Tracker household travel survey. This, in effect, uses the distributions found in the hazard models and applies an updating process to match them to Chicago mean rates.

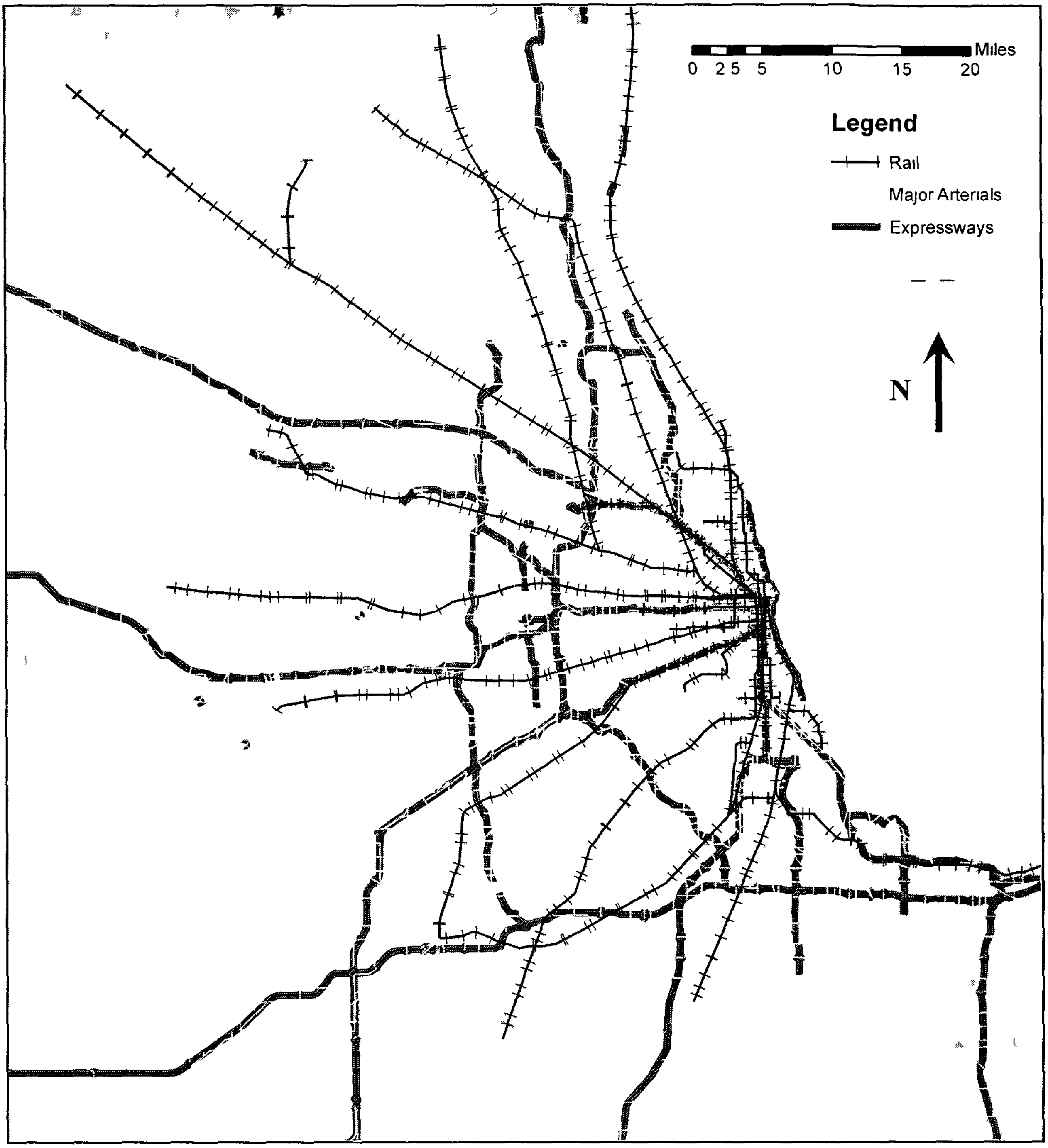


Figure 29. Chicago Area Model Region and Transportation Network

14.2. Chicago Region Simulation Results

The ADAPTS simulation for the Chicago region was run in approximately 80 hours to simulate 7 days of activity-travel planning, scheduling and execution. There were a total of 28,516,218 trips per day generated in the simulation in an average of 11,367,295 individual activity tours, for an average tour size of 2.5 activities. A more detailed analysis of the activity and travel pattern results is presented in the following sections. An example of the type of information that can be derived from the ADAPTS model is shown in Figure 30, which depicts estimated total link delay values at 8:00AM during the AM peak period. These link delays are used as an estimate of congestion in the network. The remainder of this section focuses on validating the estimated results against the existing regional model and observed traffic counts.

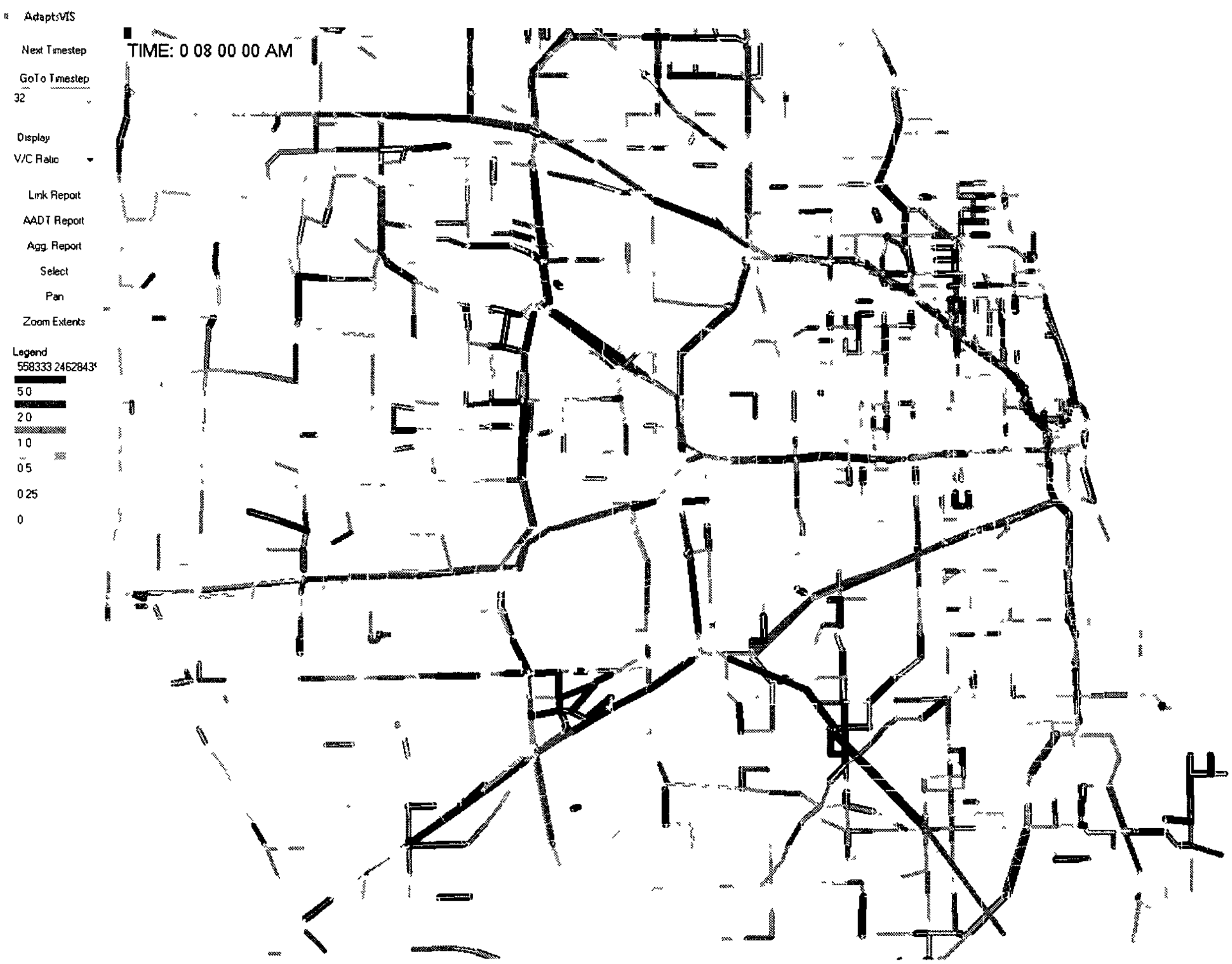


Figure 30. Link Delay During AM Peak Period (in vehicle hours)

14.3. Individual-Level Activity-Travel Pattern Characteristics Validation

After the Chicago model had completed running for the seven fully simulated days, a number of different validation analysis were performed. The first was to compare the generated activity-travel patterns to the observed patterns in the recent CMAP household travel survey (CMAP 2007) to ensure that the model is estimating reasonable activity-travel characteristics. This was done through comparing a number of different metrics including activity counts, activity durations, tour patterns and travel time distributions. The averages of these measures were compared to the weighted averages from the survey data, sometimes for the population as a whole and sometimes for population sub-groups.

The first validation performed was to look at the average daily activity rates generated from the full ADAPTS model, as was done in the validation of the activity generation model. The results of this analysis are shown in Figure 31 for the nine discretionary activity types, the two mandatory activity types and the pick-up/drop-off escort activities, which had no underlying model but were simply generated through scheduling rules. The results in the figure are averaged over all of the modeled days with error bars showing the observed standard deviations of the estimates.

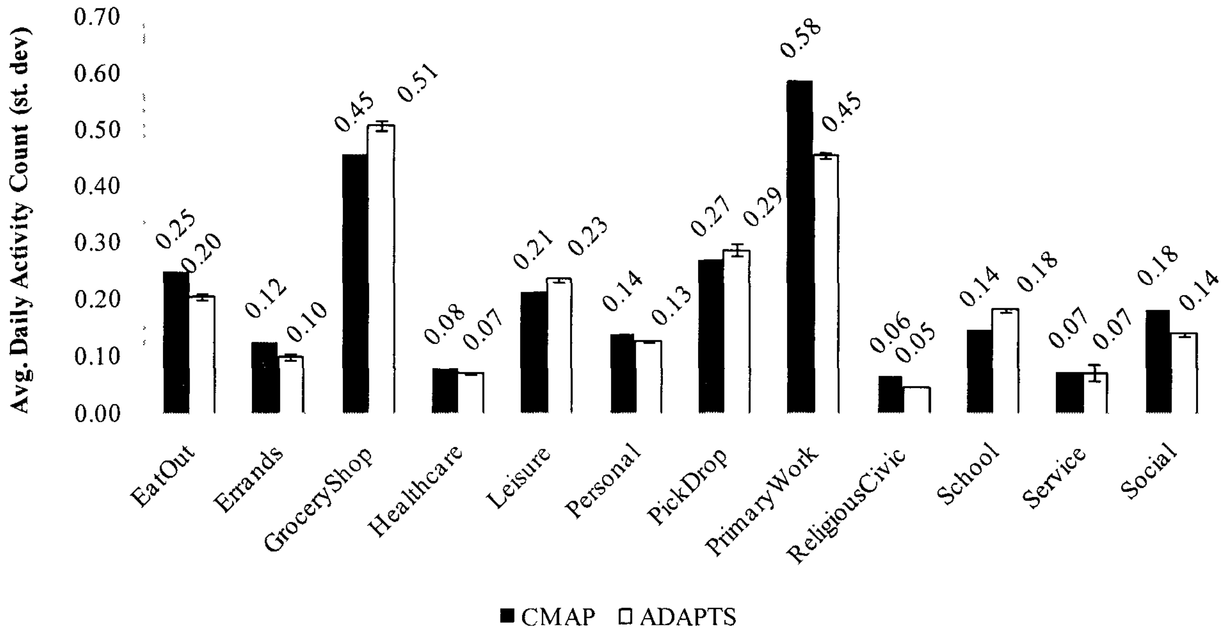


Figure 31. Comparison of CMAP to ADAPTS Daily Activity Rates

The activity count estimates show that the model replicates the observed activity counts seen in the household survey data fairly well, and more importantly that there is not much model variance in aggregate estimates such as daily activity rates. The only activity category where substantial differences were observed was for the primary work activity, with only an average of 0.45 episodes per day generated in ADAPTS versus 0.58 for CMAP. This could be due to a number of factors, including population differences or work pattern differences, such as having more short-duration or split-work activities in the CMAP data. To investigate this further, the total average daily duration spent in each activity was investigated.

The total activity duration results are shown in Figure 32 for the twelve activity types. In this figure, it is clear that on the aggregate level there is not much difference between the ADAPTS and CMAP estimates, other than that on average individuals are spending about 40 minutes less per day on work. The other activities all match well, with ADAPTS sometimes overestimating durations of short activities due to the minimum activity time threshold used in the model, which means that activities less than 15 minutes are not generated.

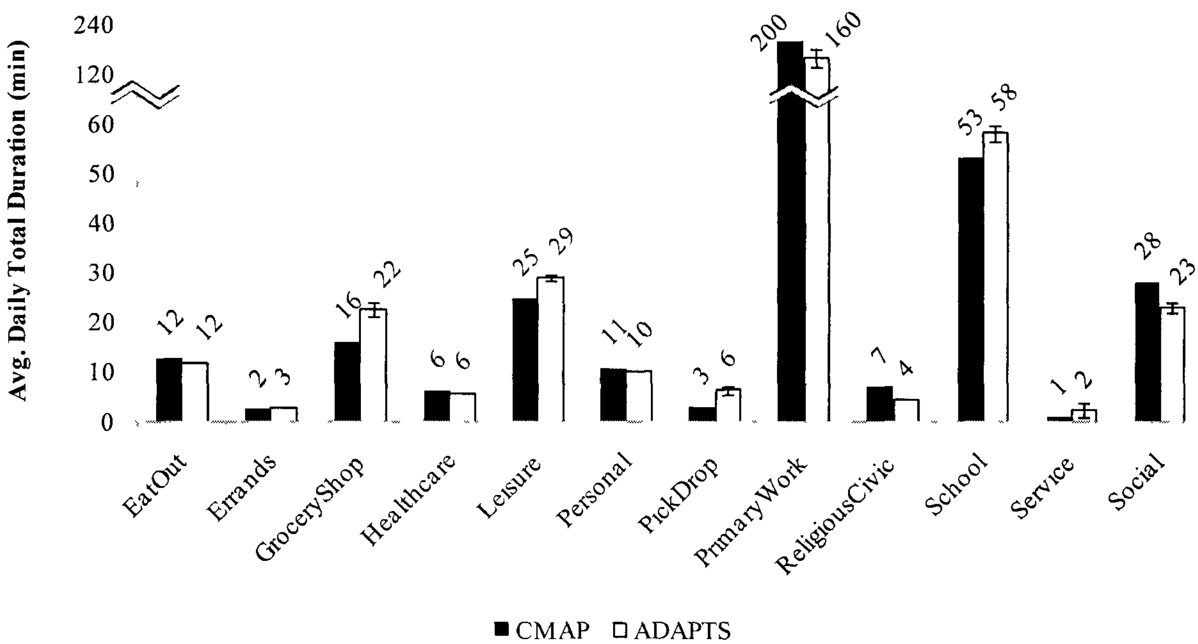
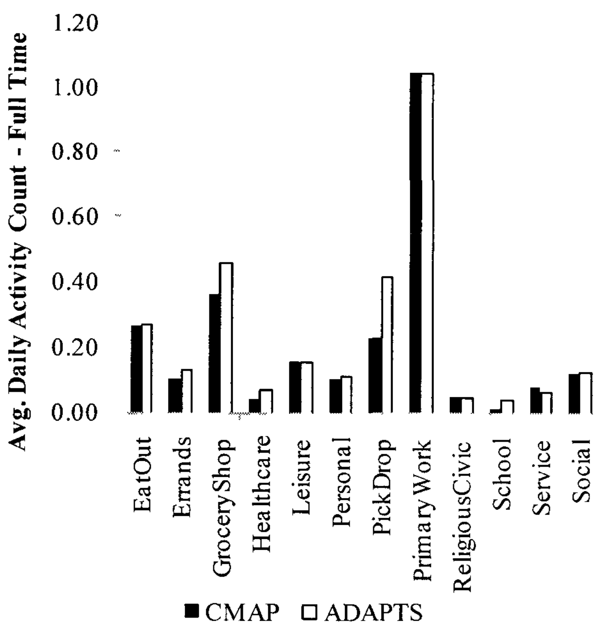


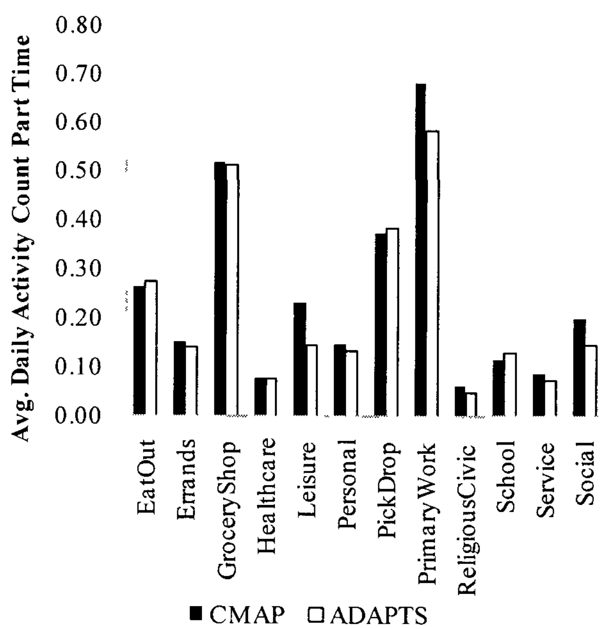
Figure 32. Comparison of CMAP to ADAPTS Avg. Daily Total Activity Duration

While the aggregate level activity pattern results were encouraging, there were some discrepancies in the primary work activity rates and durations which needed further analysis. Therefore, the same activity rate and duration analyses were performed again for population subgroups, where the individuals were split into full-time worker, part-time worker, unemployed/homemaker and students. The activity pattern characteristics for these subgroups were then analyzed in the same manner as before.

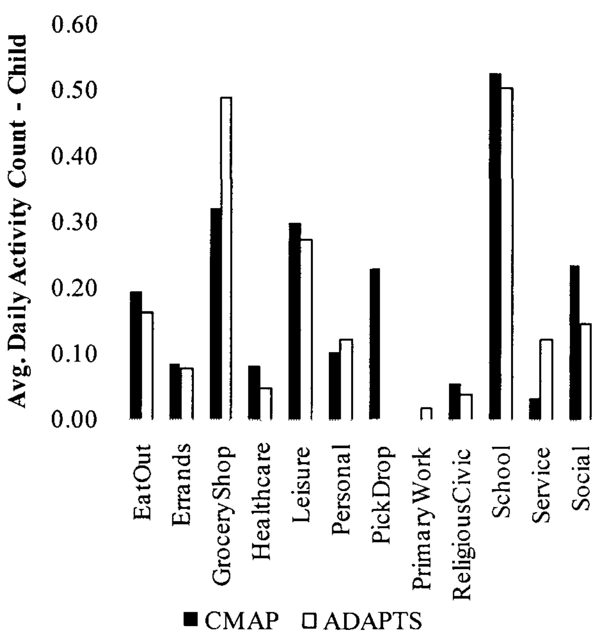
The analysis for the average activity rates by population subgroup is shown in Figure 33. These figures show that the number of primary work activities generated for full time workers (and to a lesser extent students and unemployed individuals) is accurate when compared to CMAP results, while the number of activities for part time workers is slightly underestimated (0.68 vs. 0.58 in ADAPTS). This shows that the discrepancy observed in the activity rates for the population as a whole is due more to differences in the distribution of population characteristics in the CMAP survey sample, than to errors in the ADAPTS model results. Two other substantial differences between the CMAP and ADAPTS subgroup results involve the shopping and pickup/drop-off activities. For shopping, the ADAPTS model represents the rates for employed individuals well, with only minor differences for the full-time workers. However, ADAPTS greatly overestimates the amount of shopping activities students are involved in and underestimates the shopping activities by unemployed individuals. One potential reason for this is the small sample size from the UTRACS survey on which the distribution curves are based as only adults were represented, however most students in the region are children. Extra care will be needed in future work on ADAPTS to develop children's activity models more accurately. The other discrepancy is between the ADAPTS and CMAP pick-up drop-off activity rates for students. This is more likely due to coding differences than actual errors, as ADAPTS does not consider the act of being pick-up or dropped off an activity. Therefore when an escort activity is generated it is only added to the parent's schedule.



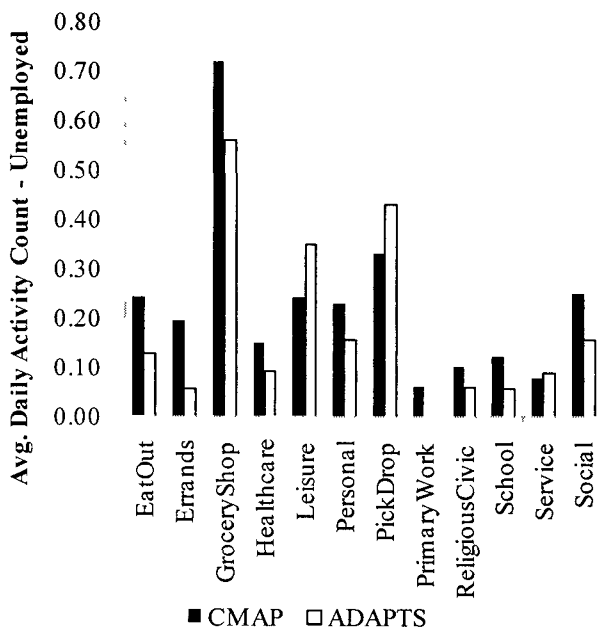
(a) Full Time Workers



(b) Part Time Workers



(c) Children

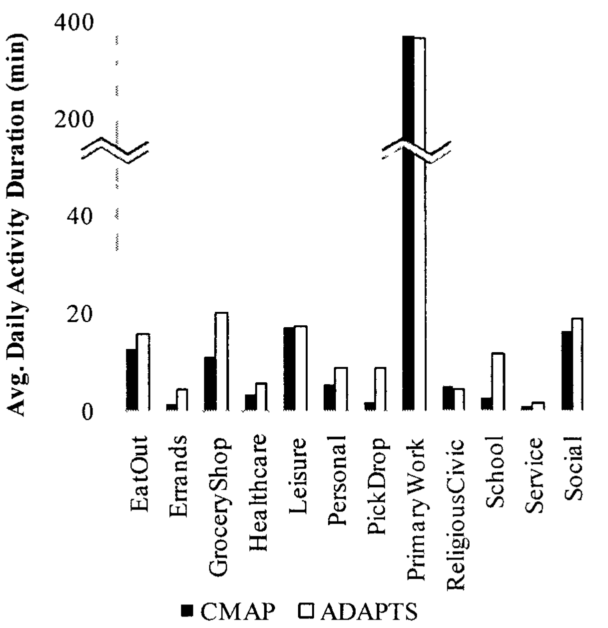


(d) Unemployed / Other

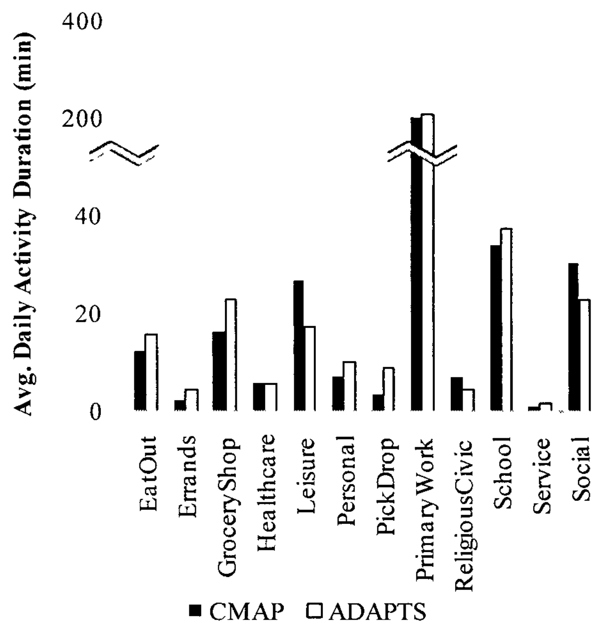
Figure 33. CMAP vs. ADAPTS Avg. Daily Activity Rates by Person Category

The average daily durations for the subpopulation groups were also evaluated, as shown in Figure 34. This analysis showed that the actual time spent in work was almost exactly the same for CMAP and ADAPTS, showing that the differences in the activity rates are mostly due to how the time is split into different activities. Most of the remaining activities match fairly well, with ADAPTS again overestimating short activities due to model limitations. However, ADAPTS does significantly underestimate the amount of time children spend socializing, for the same reasons as discussed above, and underestimates the amount of time unemployed individuals spend in school while overestimating the time they spend on leisure. Overall, however, the results show that the activity patterns observed in the CMAP survey are represented fairly well by ADAPTS.

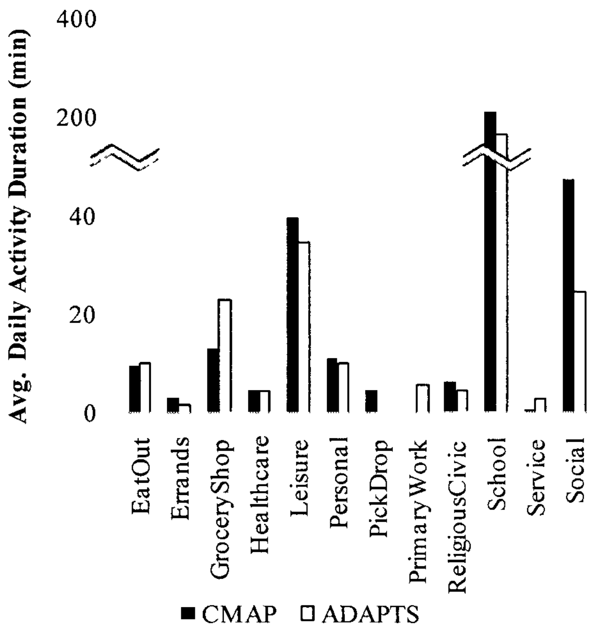
The individual trip and tour making characteristics were also validated against observed survey data for the ADAPTS Chicago model. This involved comparing the trip travel time distributions against those found in the survey data for all trips made and for different classes of trips. These results, however, need to be interpreted with caution as the survey data recorded individual estimated travel times which tend to suffer from overestimation and round-off bias (Battelle 1997). The comparison was done using 10-minute travel time bins to minimize some of the rounding error. The results for all trips and for trips to work, shopping and discretionary activities are shown in Figure 35. The travel time distributions all match fairly closely, with only the work distribution having a noticeable difference from the survey observations. Again, most of the difference appears to be underestimation of the self-reported travel times, especially for the work activity, which was not unexpected. Overall there was a mean travel time of 19.2 minutes for all trips, compared to 21.1 minutes observed in the survey, a difference of 9.9%. The ADAPTS model, then, appears to replicate the observed trip travel times fairly well, capturing the differences between travel time distributions for different activities that were observed in the survey data. The final individual level analysis looks at the characteristics of the tours formed by the scheduling model.



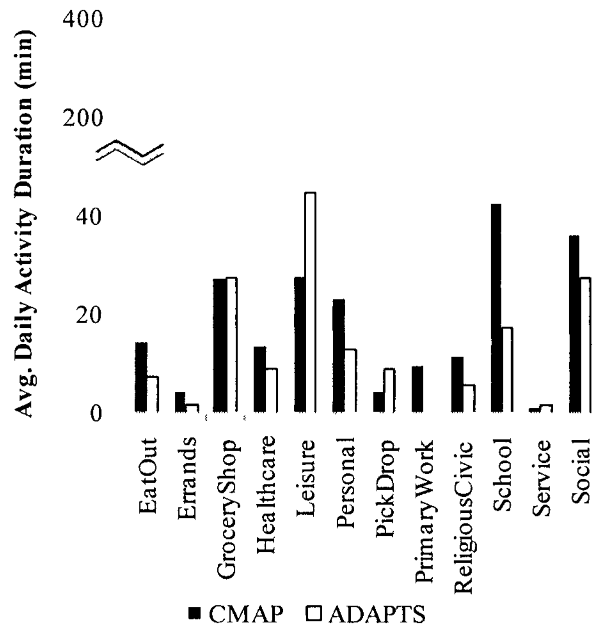
(a) Full Time Workers



(b) Part Time Workers



(c) Children



(d) Unemployed / Other

Figure 34. CMAP vs. ADAPTS Average Daily Activity Duration by Person Category

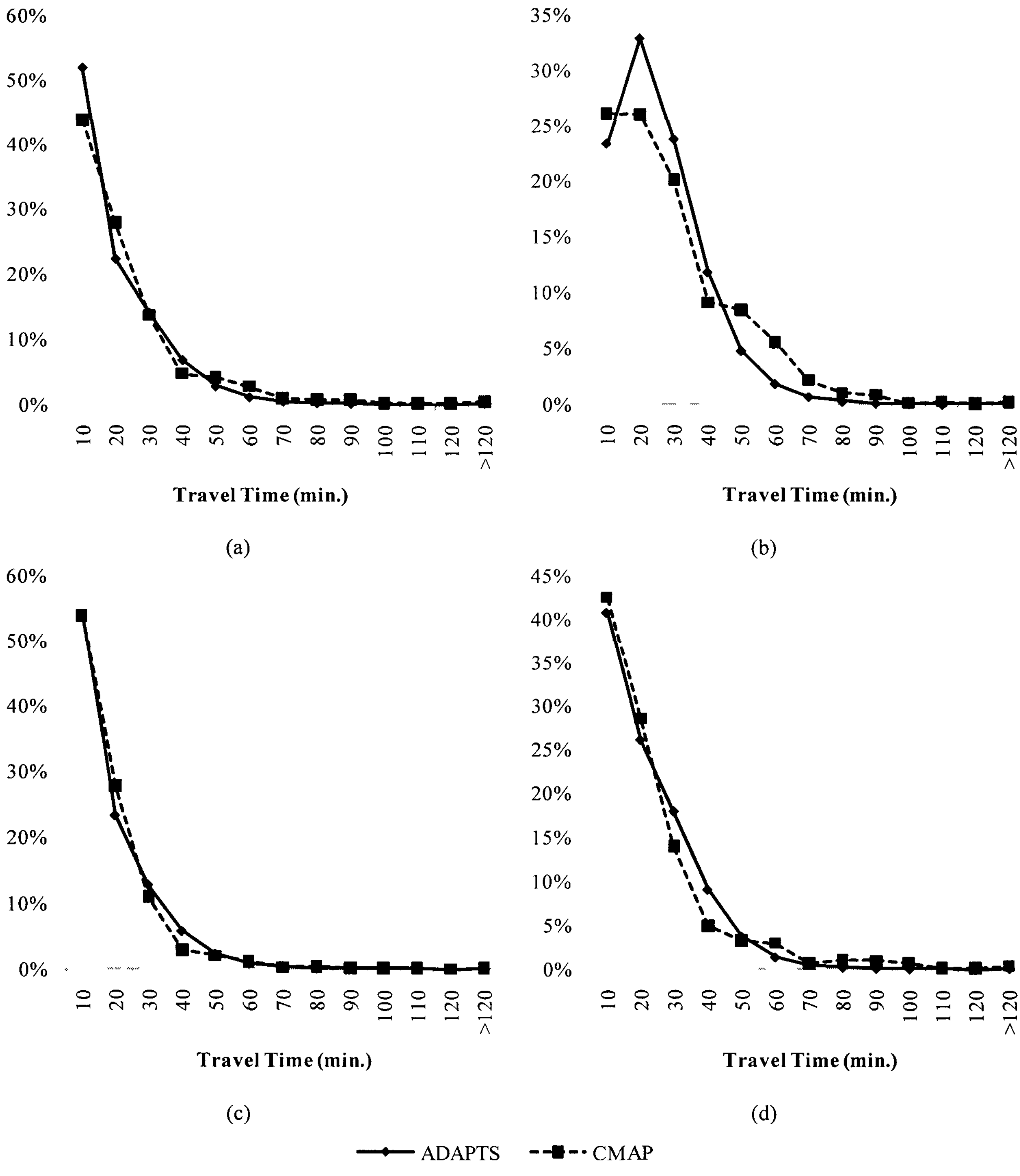


Figure 35. Comparison of ADAPTS to CMAP Travel Time Distributions for (a) All trips (b) Work Trips (c) Shopping Trips and (d) Discretionary Trips

There is no explicit tour formation model in the ADAPTS activity-based model as there would be in many of the econometric-based daily activity plan models of the type first developed by Bowman and Ben-Akiva (2001). Instead, tour formation is an opportunistic process which depends on the activity start time flexibilities and the existing schedule at the time each activity is planned. This means that as an activity enters the schedule, tour formation rules determine whether an activity will be shifted to form a tour with another activity. In addition, the results of the activity splitting process as dictated by the conflict resolution rules also result in multi-stop activity tours. These are most often seen, for example, with mid-day work splitting by a shopping, eat out, or other discretionary activity. The results of the tour formation process from the Chicago model were then tested against the tours observed in the survey data to ensure that these rules were functioning properly. The comparison can be seen in Figure 36. This comparison shows that the ADAPTS model replicates the general pattern observed in the CMAP survey, but somewhat over-represents single-activity tours and correspondingly under-represents the more complex tours with four or more activities. Fortunately, the two and three stop tours match very closely to the survey data. The tour results, then, appear to show that the scheduling rules are working well to generate activity tours. Perhaps additional rules, such as constraining the amount that in-home activities can be overlapped in conflict resolution which is currently unconstrained, will result in a better fit to the observed distributions. The tour comparison represents the final schedule level comparison made against the observed activity-travel pattern data. The remainder of the section will focus on network results compared against observed counts and the calibrated CMAP model.

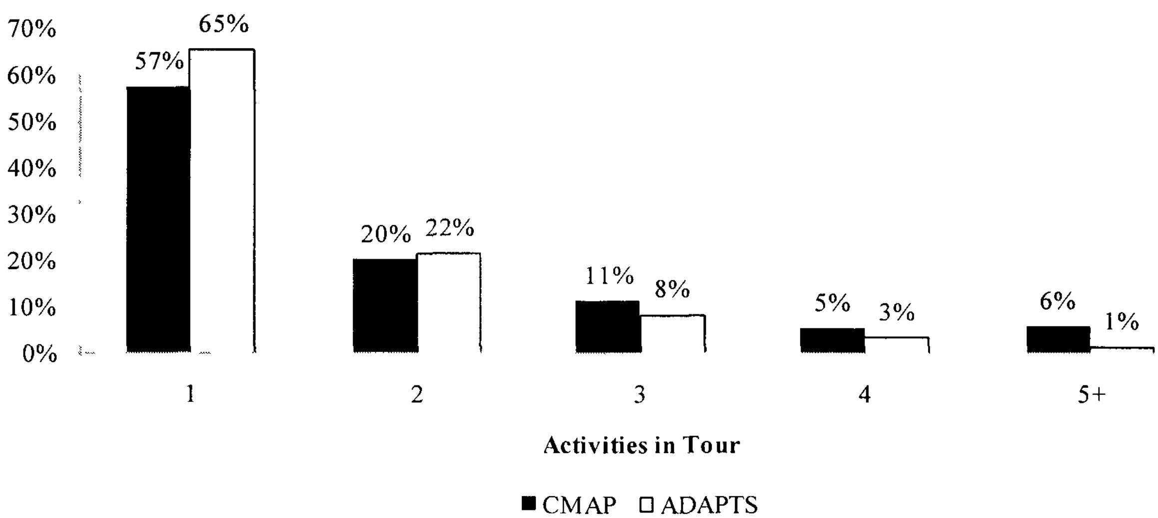


Figure 36. Tour Stops Comparison

14.4. Aggregate Region-Level Network Validation Measures

In addition to validating the generated activity-travel patterns as described in the previous section, the network assignment results obtained using the new simulated incremental dynamic traffic assignment routine also needed to be validated. Several sources of data were used to make these validation comparisons. The first data source was the CMAP regional travel demand model validation report for the 2010 baseline model (Heither 2011). This report also collected data from other sources such as Illinois Department of Transportation (IDOT) ground counts collected for the Illinois Roadway Information System (IRIS). Finally, individual simulated link data was also compared to detector data collected from highway loop detector data.

The first analysis performed was to compare the generate amount of vehicle miles traveled (VMT) by functional class on the CMAP network against the results from the latest CMAP model run, which were encoded as a variable in the network (CMAP 2010b). The results of this analysis are shown in TABLE XXIV. The results show that overall the comparison by facility type is good. ADAPTS over-simulates the expressway VMT to a certain extent, but the arterial/local counts are nearly the same. It should be noted here that the "Centroid Connector" facility type from the CMAP network has been combined with the arterial facility type as the centroid connectors are supposed to represent travel on local streets. However, in ADAPTS, trips are not generally routed from zone centroids, but rather they start at random points inside the zone, so that centroid traffic is not a significant part of the total traffic. Therefore centroid and arterial traffic has been combined to give a more reasonable comparison between the two models. Also important to note is that this analysis is limited to the six-county Chicago region and not the CMAP analysis region as a whole, as the other counties are not simulated in ADAPTS.

TABLE XXIV
COMPARISON OF CMAP TO ADAPTS MODEL VMT

	Counts by Facility			Distribution by Facility	
	CMAP	**ADAPTS**	**% diff.**	**CMAP**	**ADAPTS**
Arterial	136,941,077	135,168,017	-1%	71.0%	66.6%
freeway	50,564,481	60,605,607	20%	26.2%	29.8%
ramp	2,091,995	2,884,679	38%	1.1%	1.4%
express	2,603,039	3,169,270	22%	1.3%	1.6%
freeway connect	584,519	988,853	69%	0.3%	0.5%
ramp-meter	133,526	236,046	77%	0.1%	0.1%
Total	192,918,638	203,052,473	5%	100.0%	100.0%

Taking the above analysis a step further, the results by functional class were split into counties to determine the share of total VMT by each county and aggregated functional class (i.e. interstate, arterial and local). These results were then compared against the distributions found in the CMAP validation report (Heither 2011) for both the CMAP model and observed IDOT ground counts. The results are shown in TABLE XXV. Again, the results show that the ADAPTS model performs well in distributing the VMT to the various counties and facility types. In fact the ADAPTS model outperforms the CMAP model in assigning total VMT to Cook, Kane and McHenry counties and is closer in overall distribution by facility type to the observed data, with vary small differences in percentage of trips assigned to highways and arterials. Next, the results of a screenline analysis performed on the assigned network were compared against the observed traffic counts from the IDOT IRIS system to further validate the observed distribution of trips. The screenlines used for the analysis are shown in Figure 37.

TABLE XXV
VMT SHARES BY COUNTY AND FACILITY TYPE

County	Func. Class	Observed	CMAP	ADAPTS	% Error CMAP	% Error ADAPTS
Cook	Interstate	19%	17%	21%	-10%	12%
	Arterial	37%	36%	34%	-3%	-7%
	Total	**56%**	**53%**	**56%**	**-5%**	**-1%**
DuPage	Interstate	5%	4%	6%	-20%	15%
	Arterial	10%	11%	10%	5%	-1%
	Total	**15%**	**15%**	**16%**	**-3%**	**4%**
Kane	Interstate	1%	1%	1%	46%	-4%
	Arterial	5%	6%	6%	24%	23%
	Total	**6%**	**8%**	**7%**	**28%**	**19%**
Lake	Interstate	2%	2%	1%	-4%	-44%
	Arterial	8%	8%	7%	6%	-10%
	Total	**10%**	**10%**	**8%**	**4%**	**-17%**
McHenry	Interstate	0%	0%	0%	0%	0%
	Arterial	4%	4%	4%	5%	-11%
	Total	**4%**	**5%**	**4%**	**14%**	**-10%**
Will	Interstate	4%	3%	3%	-25%	-26%
	Arterial	5%	7%	7%	34%	36%
	Total	**9%**	**10%**	**10%**	**8%**	**9%**
Region	Interstate	31%	35%	32%	13%	3%
	Arterial	70%	65%	68%	-7%	-3%

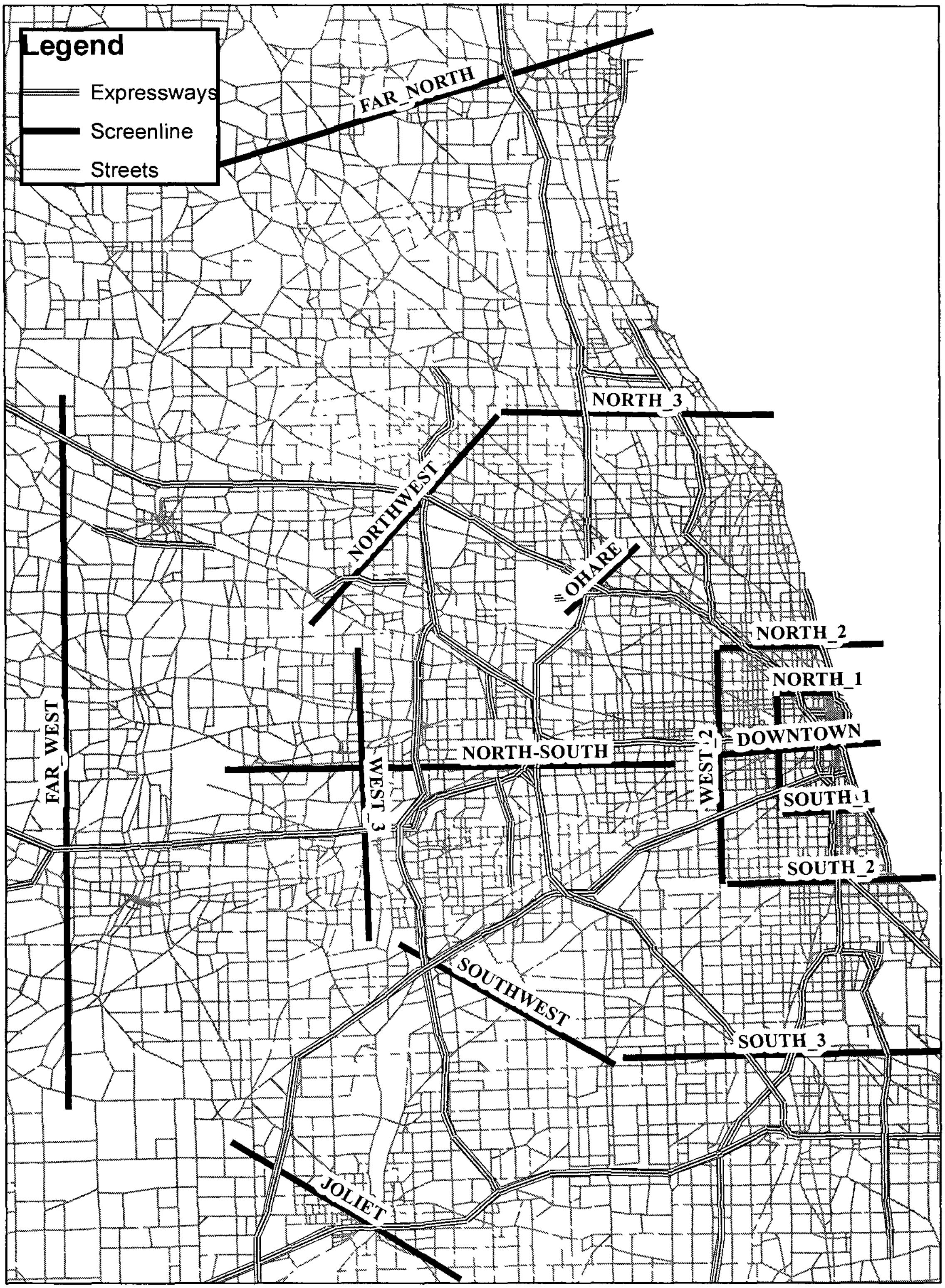


Figure 37. Screenlines on Chicago Road Network

The screenlines selected for analysis bisect all of the major corridors in the Chicago region. The trips crossing each screenline through all network links which the screenline passes through were summed up for the ADAPTS and IDOT data. The comparison is shown in Figure 38. These counts represent a more detailed validation of the aggregate network results than simply summing VMT by county. The ideal, however, would have been to compare links in the IRIS system to ADAPTS link volumes directly. However, the different format of the network, where the ADAPTS network uses the abstract CMAP network and the IDOT network follows closely to actual road centerlines, prevented this comparison. However, this mismatch is not significant for screenline analysis. The screenline results show that ADAPTS is slightly overestimating the number of trips passing through the screenlines when compared to the IDOT counts, with 11.7% more daily trips overall. This could be due to the IDOT counts being somewhat outdated, with most having been collected around 2005 or 2006. However, the distributions follow somewhat of the same pattern, with the most trips passing through the "Northwest" and "North-South" screenlines, and the least trips in the far suburbs.

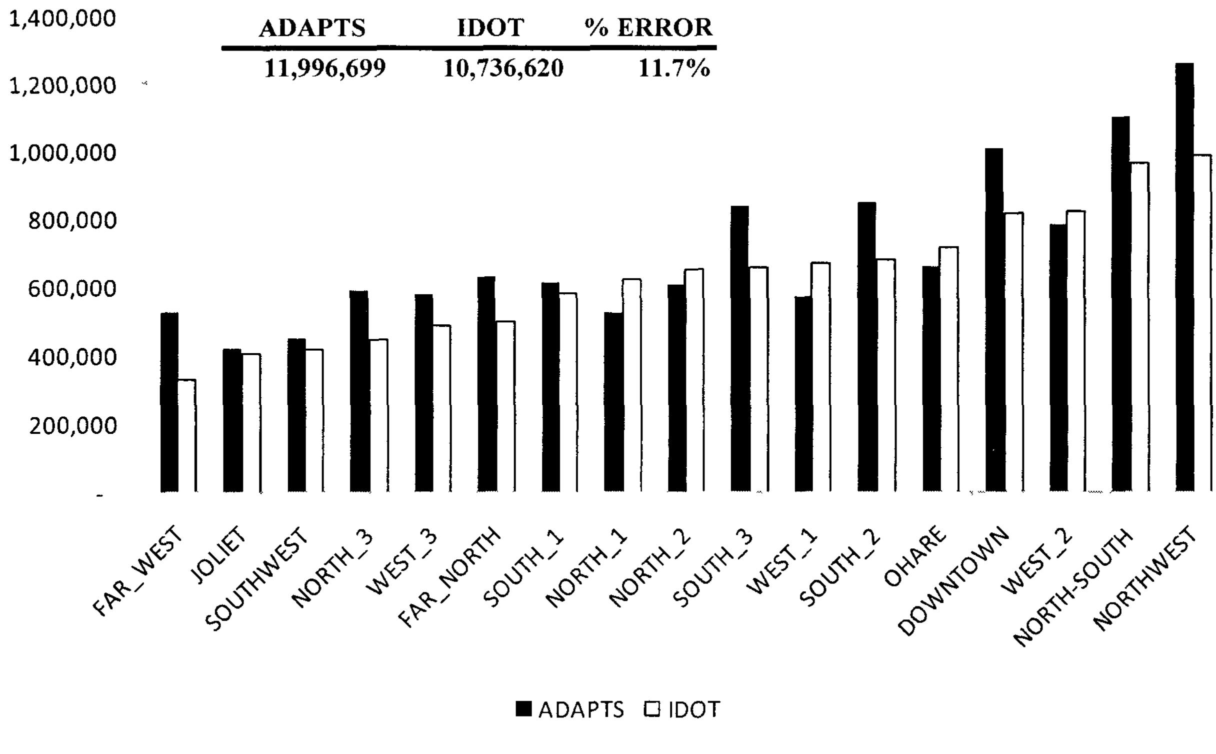


Figure 38. ADAPTS vs. IDOT Screenline Count Comparison

14.5. Disaggregate Network Validation

The traffic results obtained from the ADAPTS simulation model run were also compared on the disaggregate network level to the CMAP model and to observed highway loop detector counts The comparison to the CMAP average vehicle mile traveled per link is shown in Figure 39, and is a standard output of the AdaptsVis analysis program The figure shows the absolute percentage difference in link VMT for the network The close up of the downtown area is shown in the inset, and shows that the ADAPTS and CMAP models match fairly closely in terms of downtown traffic where the highest flows are observed The greatest differences between the models were found around outlying areas southwest and west of the downtown region perhaps due to missing trips from the non-modeled outlying counties heading in to the city The greatest difference in the city was a fairly substantial overestimation of travelers using the Ohio Street spur into the I90/94 expressway, seen at the top of the inset It should be noted however, that the CMAP results are also derived from a model and do not necessarily represent more accurate estimates than the ADAPTS results

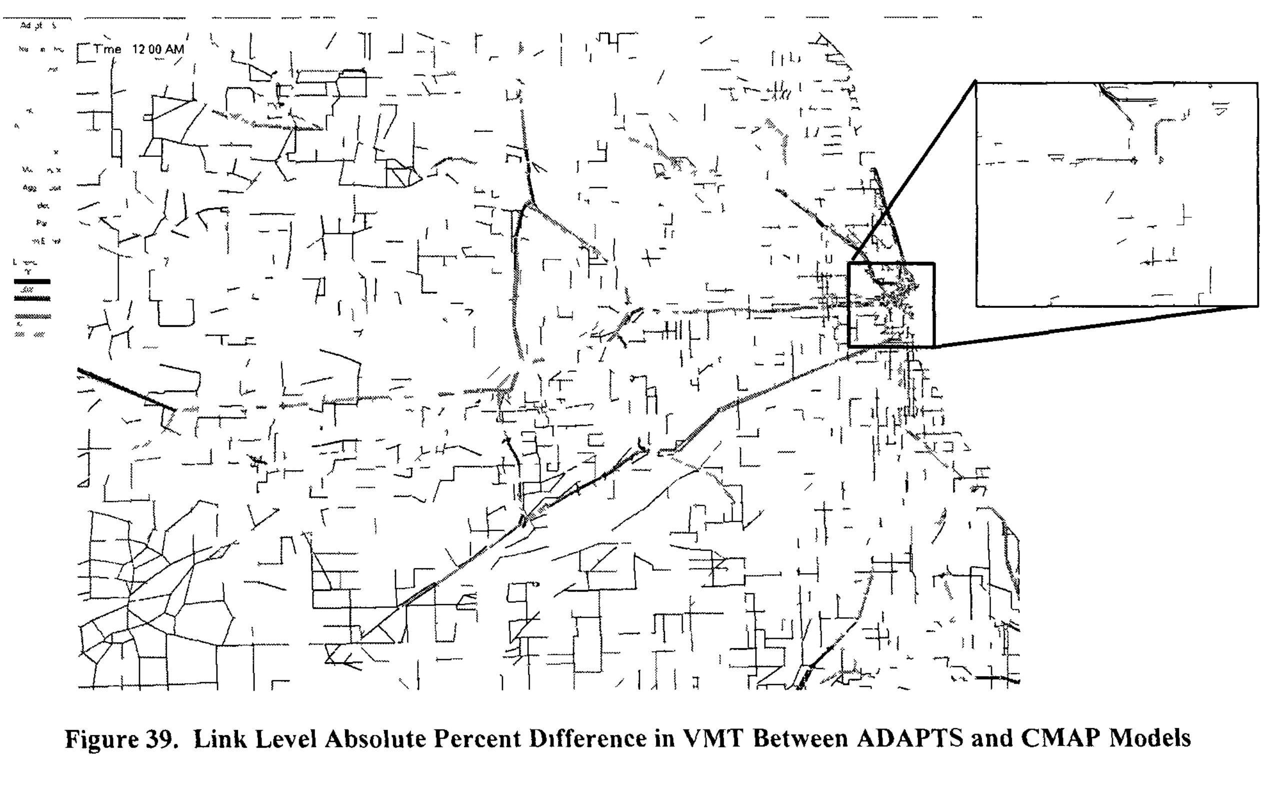


Figure 39. Link Level Absolute Percent Difference in VMT Between ADAPTS and CMAP Models

The link-level results shown in Figure 39 above were aggregated into arterial and non-arterial facilities and various volume ranges, to estimate the average differences between the CMAP and ADAPTS results. The percent root mean squared error (%RMSE) was calculated for each facility-volume range category and the results are shown in TABLE XXVI. The results show that there are some differences between the estimated volumes from the CMAP and ADAPTS models. The average difference, however, decreases as the link volume increases, with only a 36% RMSE value for the large expressway links, which ADAPTS tends to overestimate.

TABLE XXVI
LINK-LEVEL RESULTS FOR ADAPTS VS. CMAP

Facility	Volume	AADT CMAP	AADT ADAPTS	RMSE	%RMSE
Arterial	< 10,000	4,156	4,532	3,461	83%
Arterial	10,000-30,000	15,919	17,446	7,877	49%
Arterial	>30,000	34,449	40,379	15,659	45%
Expressway	< 25,000	9,630	13,969	9,152	95%
Expressway	25,000-50,000	37,383	43,873	18,395	49%
Expressway	50,000-100,000	69,624	89,597	33,711	48%
Expressway	> 100,000	127,637	162,642	46,032	36%

Finally, link volumes over time derived from the ADAPTS simulation were compared to highway loop detector data which had been previously collected, to determine how well the time distribution of the link volumes from the model match to actual ground counts. The comparisons were performed for several links, including inbound I290 at East Avenue, inbound I94 at Dempster Avenue and inbound I290 at St. Charles Road. The analysis was limited to count stations which had detectors in all lanes to avoid the need for correction factors.

The comparisons show that the estimated link traffic volumes generally follow a similar distribution to the observed traffic counts. However, the ADAPTS simulated volumes tend to have higher peak values then the actual observed counts. This could possibly be a result of the simulation method used, where the link volumes can exceed physical capacity and can potentially give higher volume results than would otherwise be expected. This could be corrected when a more detailed traffic simulator is integrated into the ADAPTS model system.

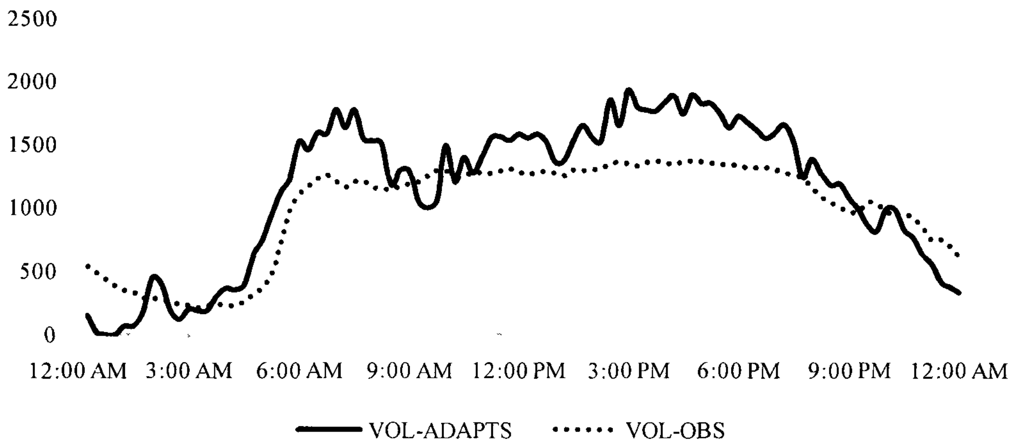


Figure 40. Traffic Volumes at Inbound I290 at East Avenue.

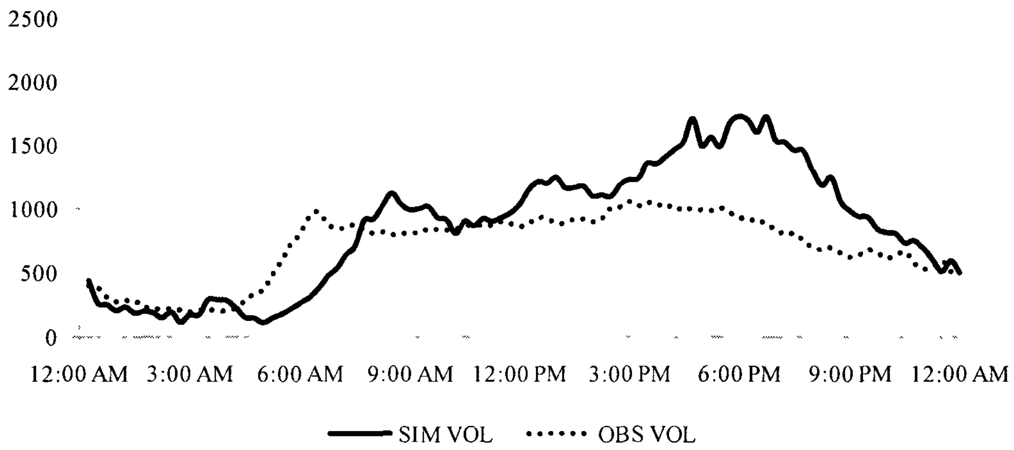


Figure 41. Traffic Volumes at Inbound I290 at St. Charles Road.

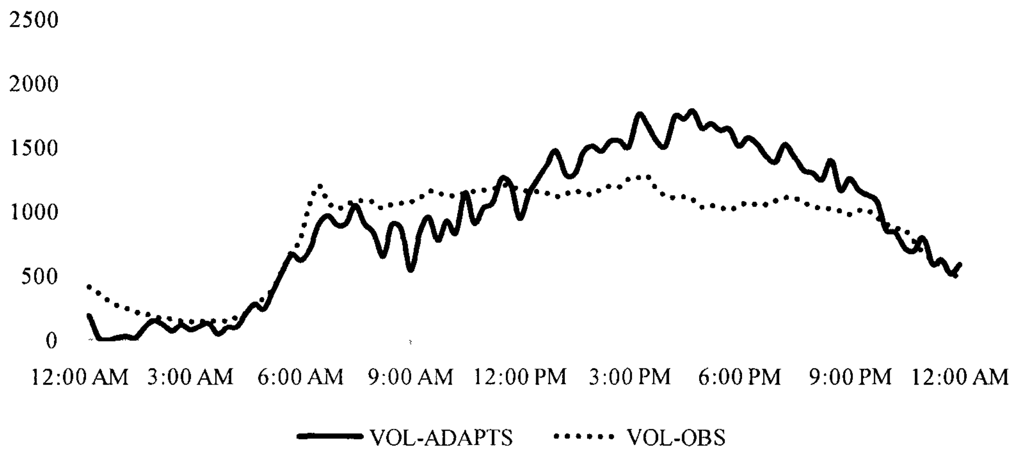


Figure 42. Traffic Volumes at Inbound I94 at Dempster Ave.

Overall, the ADAPTs model appears to validate fairly well to both the existing regional model results as well as the observed data available for the region. This is especially significant as no network calibration has been performed in the current implementation of the Chicago model. In addition, the network updating is currently greatly simplified, with decisions made based on only two LOS skims which are updated at a single fixed point in the peak and off-peak periods. As more research is completed on integrating network simulation into activity-based models the network results should be improved substantially. This could be introduced through learning models so that experienced travel times are used for more than updating LOS skims. Additionally, more physically realistic simulation models of travel, such as cell-based or car-following models, could produce more realistic travel times and reduce aggregation error compared to using 15-minute link volumes-delay functions.

15. CONCLUSIONS AND FUTURE WORK

This work has described in detail the development of a new dynamic activity based model called the ADAPTS model. This project was started to address several observed gaps in the research on activity-planning and scheduling models and to advance the state of current activity-based models used for planning and policy analysis. The primary goal of the work was to develop an activity-based model which focused on the dynamics of the planning, scheduling and execution of activity-travel patterns. In addition to developing a fully-functional dynamic activity-based model, research into observed planning behavior and data collection on some of the planning and scheduling processes have led to a new understanding of these phenomena.

Several research gaps regarding activity-based modeling were identified in an initial review of previous research and existing models, which motivated the development of ADAPTS. The most significant issue observed was that most models were designed to estimate executed patterns of activities, with no consideration for modeling the underlying process of how those activity patterns were actually arrived at (Garling et al. 1996). And, even in models intended to represent the activity-scheduling process, simplifications due to lack of data, were often necessary. This means that representations of planning and scheduling dynamics are not included even in many rule-based, computational process models (Litwin and Miller, 2005). The scheduling process is simplified through simple heuristics which assert the priority of activities, the order in which activity attributes are planned, the order in which activities enter the schedule, and so on, with no reference to empirical data.

Therefore, another motivating factor behind the work was the growing effort to collect data regarding the activity planning and scheduling process. Several surveys have recently been completed which go beyond collecting only the revealed activity-travel patterns. These studies, such as CHASE (Doherty et al. 2004), REACT! (Lee and McNally, 2001) and OPFAST (Lee-Gosselin 2005), attempted to observe the activity scheduling and rescheduling process. A similar study conducted by Ruiz (2005) focused specifically on activity conflict resolution. A more qualitative effort was also recently undertaken by Clark and Doherty (2008), where a survey similar to the one described in Part II of this thesis (i.e. preplanning survey followed by GPS prompted recall) was conducted, but was then followed by interviews to ascertain the reasoning behind some of the changes observed. All of these surveys, combined with the UTRACS survey collected as a part of this work, have provided much data on the activity planning and scheduling process. Some initial models have been developed using process data for limited aspects of activity planning, such as activity planning horizon (Mohammadian and Doherty, 2005) and conflict resolution (Ruiz and Timmermans, 2006). This data, however, has not been utilized to any great extent in the development of comprehensive activity-based models which represent the activity planning process.

These observations were the primary driving force behind the development of the ADAPTS model. However, in the course of developing the full activity-based model system, several fundamental advances in the basic understanding and modeling of planning behavior were also made. Greater understanding of the dynamics underlying activity generation and planning, and of how planning decisions regarding different aspects of the process impact each other, contribute to the general state of knowledge regarding traveler behavior. In addition, a more detailed knowledge of the handling of activity-conflict resolution strategies was developed. Possibly, however, the most important observation made regards the transferability of many of the planning and scheduling processes.

The activity generation model developed for ADAPTS showed that activity generation can be fundamentally thought of as a competition between different activity needs which change over time, as Timmermans and Arentze (2006) have proposed. The competing hazards framework adopted for this model captures how the needs for each activity influence the needs for the other activities in a proportional hazard formulation. The results show that generally increased hazards for certain discretionary activities tend to increase the hazard of other discretionary activities, mostly involving eating out, socializing and leisure activities. In a similar manner, shopping and service activities also tend to cluster together into maintenance-type tours. Meanwhile, these discretionary and maintenance activities tend to delay each other, so when the need for one is high, the others are put off. Another aspect of the activity generation process revealed in this work was found through the use of the additive Weibull "bathtub curve" for the baseline hazard functions for each activity. The significant parameter estimates for the baseline hazard parameters, for all but the socializing activity, verify the hypothesis that there are multiple activity generation processes at work. These are the trip-chaining impetus represented by the high initial hazard with rapidly decreasing value ("the infant mortality portion of the hazard curve") and the needs-growth impetus represented by the slowly increasing hazard over time ("the aging portion of the curve"). These results get at the fundamental dynamic process of activity generation and how it changes over time, and represent a significant step in advancing activity generation models.

Another aspect of the activity planning process addressed in the work was the underlying dynamics of the activity planning itself. The dynamics of planning were modeled by estimating how the timing of the planning of the activity and its attributes are handled given different personal and scheduling factors. A framework for the estimation of the flexibilities and plan horizons for the overall activity and its attributes was developed and the models estimated, producing insight into the activity planning process. The results show the necessity of relaxing the rigid, sequential models typically used to plan activity attributes in activity-based models. A byproduct of the model was an estimate of the correlations between various attribute flexibilities as well as between the attribute plan horizons. These results showed that for flexibility there was moderate positive correlation between timing and interpersonal choices as expected (i.e. if an individual is more flexible on when the activity can start there is more flexibility in who can be involved due to relaxed scheduling constraints). Meanwhile there was a small negative correlation between the timing and location, meaning if one is flexible the other tends not to be. The model then demonstrated the importance of the flexibility results in the activity and attribute planning horizon with inflexible attributes generally requiring more advanced planning. Another important aspect of this planning process model was some evidence of transferability with the model performing well when compared against activity plan horizon and attribute flexibility results from the CHASE (Doherty et al. 2004) and OPFAST (Lee-Gosselin, 2005) surveys, with the model generally able to estimate the observed values better than null model expectations.

In the course of model development, the influence of planning dynamics on activity attribute models was also investigated, through the development of a new destination choice model. This represents the fundamental underlying principle behind the ADAPTS model development, namely that planning order and planning time influence planned outcomes. This was shown in the case of the destination choice through the development of a new "plan-constrained" destination choice model. This model is derived from the work in PCATS (Kitamura et al. 1997) on space-time constrained attribute choices. This work extended the constraints from a simple sequential process where gaps in space-time prisms are filled activity by activity to one where the constraints are defined by the previous activity attributes and the following fixed activity attributes, to a full plan-time based space-time constraint. The constraints in each mode are calculated in a similar fashion; however, the activities which contribute to the constraints in this model depend on when they were planned, instead of assuming a linear plan order. The estimation and implementation of the model showed marked improvement in correct predictions and travel time distribution when compared to an implementation of a fixed constraints model which ignores the activity plan time. This work demonstrates the viability and value of using activity and attribute plan horizons in attribute choice models and will be extended to all aspects of activity choice in the future.

A final advance in the understanding of the activity planning and scheduling process relates to the decision making process regarding conflict resolution in scheduling. A set of conflict resolution rules were estimated using observed scheduling process data collected in the CHASE (Doherty et al. 2004) survey. The conflict resolution model demonstrated that resolution strategies are selected mainly based on the location of the conflict and some basic activity and conflict attributes, such as the planning horizon, travel requirements and durations of the activities and the type of conflict and amount of overlap. As noted before, the selected strategies seem to be largely independent of the socio-demographics of the individual. The resolutions strategies represented in the model allow activity scheduling rules of the type used in TASHA (Roorda et al. 2003) and others to be based on how individuals are expected to resolve conflicts in certain situations rather than limiting the rules to certain conflict types or trying several resolution types in a fixed order. This formed the basis for the scheduling rules developed for ADAPTS.

It is felt that all of these advances make for a substantially more behaviorally sound and realistic activity-based model which will be useful for testing a wider range of transportation policies and making more reliable forecasts for future travel demand. Another important benefit of models of this type is the greater potential for transferability. Many of the underlying planning and scheduling processes seem to be fairly transferable to different contexts, at least as observed for the planning horizon, flexibility determination and the conflict resolution process. Many of the process models show limited dependence on socio-demographic characteristics and so perhaps represent a more basic process that individuals share across different contexts and that revealed patterns differ as a result of different constraints and opportunities related to the different contexts. This would, if proven, make for more reliable forecasts as the model results would depend only on how well the future context could be estimated.

Beyond making advances in the understanding of the activity planning and scheduling process, the work in ADAPTS has also advanced the state of integration between activity-based models and traffic assignment routines. As far as the author is aware, ADAPTS is the first functional activity-based model to directly integrate with traffic simulation in a dynamic fashion where the assignment results feedback continuously to the planning and scheduling model. Several activity-based models have recently been integrated with a dynamic traffic assignment routine, Castiglione et al. (2010) for example. These integration efforts, however, are not dynamically integrated with feedback to the activity model, but rather take one day of estimated activity plans, route and simulate them, then iterate this process until convergence is reached. ADAPTS is the first model where at every step of activity planning, current traveler experiences are used for the next timestep, representing a significant advance in activity-based modeling. This allows for more realistic activity-travel patterns as schedules are updated based on simulated travel results, and is a significant advance in activity-based modeling compared to using static time-of-day based traffic assignment.

The development of the ADAPTS activity-based model and traffic simulation represents a significant step in advancing the state of rule-based activity-travel models toward including more realistic representations of planning and scheduling dynamics. The development of the various model components has revealed different aspects of traveler planning behavior especially with regards to the timing of planning decisions. In addition, the full integrated planning and travel simulation model was shown to perform well when compared against existing model results for the Chicago region in the baseline model year. However, several significant areas of future work and analysis remains to be completed before the ADAPTS model is fully realized. As far as completing the ADAPTS model, the remaining work includes the finalization of the various model components, the inclusion of social-networking and joint activity scheduling to extend the scheduling model beyond just individual level activities, and improvements to the network assignment procedures. Work also remains on validating the completed model, especially in terms of the output sensitivities to planning and scheduling results and in validating using non-baseline year scenarios.

Several of the existing ADAPTS model components need to be updated in the future, including the time-of-day and duration choices and the mode-choice model. The current time-of-day model simply uses random draws from observed start-time and duration distributions found in household travel survey data. These random draws should eventually be replaced with multivariate choice models, which can account for factors such as schedule constraints, individual characteristics and household needs when making the time-of-day decision. The durations, meanwhile can be replaced with either a hazard-based or utility-based model to determine how much time should be spent on each activity. The mode-choice model also needs updating as it is used directly from the CMAP travel demand mode (CMAP 2010b). As such the model was designed to consider only trip-based characteristics and lacks sensitivity to personal characteristics or activity and tour based factors. A more advanced model is therefore needed. Whatever the final format of the models developed for these various activity attributes, it is important that the models consider the planning constraints imposed by the activity planning dynamics modeled by ADAPTS.

The most significant remaining work in the ADAPTS model, however, involves joint activity scheduling and social networking. The current model contains only simple joint activity scheduling rules for handling child-escort activities. These rules will eventually be extended to account for both intra-household and inter-household joint activity scheduling, especially for activity types which are commonly done jointly such as eating out, socializing, recreation, etc. This will require an expanded rule-set for conflict resolution which includes a bartering mechanism for resolving scheduling conflicts between individuals. In other words, when trying to add an activity to more than one schedule, many more possible resolution strategies and limitations apply which need to be accounted for. For example, often when multiple people are scheduling an activity, the needs of one individual will control the resolution to a greater degree than others. This can occur either because one person is busier, more constrained, has different time valuations, or any number of other reasons, which will need to be modeled. This is a topic of growing importance in travel demand modeling and has recently begun to receive more attention; see Ettema et al. (2011) for example. Party composition modeling for inter-household activities will also require estimates of the formation of social networks between agents, to select appropriate agents to match for joint-activities. Survey work and empirical analysis of the formation of social network will likely lead to usable models of this phenomenon which can be incorporated into activity-based models. Some examples of data collection efforts regarding social networks and social interactions include Carrasco et al. (2008) and Van den berg et al. (2010), which can potentially be used for this purpose.

Beyond the activity planning stage, ADAPTS can also be improved in several ways in terms of the network assignment procedures utilized in the model. The first improvement would be to include more realistic transit mode characteristics and network data into the model. The current ADAPTS system does not simulate transit trips, but merely uses the transit skim travel times as the travel results for transit trips. The inclusion of transit simulation, as well as the inclusion of additional motorized and non-motorized modes in the simulation, would improve the traffic simulation results. Additionally, the model can also be extended to include more detailed representations of external and truck traffic, rather than relying on the fixed volumes from the regional travel demand model. Finally, the travel simulator utilized in the network assignment routines should be improved. The current routine uses a macroscopic simulation, which is a volume-delay based method that is not very representative of actual network conditions. This simulator could be replaced with a macroscopic queue-based model, or a more detail mesoscopic representation of travel such as the cell-based formulations found in the TRANSIMS (Nagel, 1996) model . A more detailed representation of travel, coupled with a reduced assignment time-step size would improve the network results substantially and is expected to be a significant component of future work on ADAPTS.

Finally, a concerted effort needs to be undertaken to estimate the sensitivity of the model results to changes in planning behavior and planning constraints. This would involve applying the model to various policy scenarios to observe how the policies impact travel demand results. The hypothesis that travel demand is dependent on activity and travel planning behavior, and that consequently changes in these behaviors can change activity-travel patterns, was the major motivating factor underlying ADAPTS development. Therefore the final model needs to be thoroughly tested using a variety of policy scenarios to ensure sensitivities to planning behaviors are represented. In addition, forecasting tests should be conducted, first using backcast scenarios against known data and then for forecast scenarios to compare against forecast results from four-step models. These efforts will ensure that ADAPTS is behaving as intended and will make valuable contributions to the field of travel demand forecasting.

CITED LITERATURE

Abbring J H and G J Van den Berg, (2007), The unobserved drtibution in duration analysis, Biometrika 94, 1, pp 87–99

Abdel-Aty M , R, Kitamura and P Jovanis (1995), Investigating the effect of travel time variability of route choice using repeated-measurement stated preference data, Transportation Research Record, 1493, pp 39-45

Abrevaya J and J A Hausman, (1999), Semiparametric estimation with mismeasured dependent variables An application to duration models for unemployment spells, Annales d'Economie et de Statistique, No 55/56, pp 243-275

Anggraini, R T A Arentze and H J P Timmermans (2007) Refining Albatross Modeling Household Activity Generation and Allocation Decisions Using Decision Tree Induction World Conference on Transport Research Society

Ansah, J A (1977) Destination choice set definition and travel behaviour modeling, Transportation Research, 11, 127–140

Arentze, T and H Timmemans (2000) *ALBATROSS – A Learning Based Transportation Oriented Simulation System* European Institute of Retailing and Services Studies (EIRASS), Technical University of Eindhoven

Arentze, T and H J P Timmermans (2007) Robust Approach to Modelling Choice of Locations in Daily Activity Sequences, Proceedings of the 86th Annual Meeting of the Transportation Research Board, January 2007

Arentze, T , H Timmermans and F Hofman (2007) Creating synthetic household populations - Problems and approach *Transportation Research Record Journal of the Transportation Research Board*, 2014, National Research Council, 85-91

Arentze, T , H Timmermans, D Janssens, and G Wets (2006) Modeling Short-term Dynamics in Activity-Travel Patterns From Aurora to Feathers Paper presented at the Innovations in Travel Modeling Conference Austin, TX, May 2006

Arentze, T A and H J P Timmermans (2007) A Dynamic Model for Generating Multi-Day, Multi-Person Activity Agendas Approach and Illustration 86th Annual Meeting of the Transportation Research Board (CD), Washington D C January 2007

Arentze, T A and H J P Timmermans (2009) A need-based model of multi-day, multi-person activity generation Transportation Research B 43, 251-265

Ashford, J R and R R Sowden (1970) Multi-Variate Probit Analysis *Biometrics*, 26 (3), 535-546

Auld, J A , A Mohammadian and M Roorda (2009c) Implementation of a Scheduling Conflict Resolution Model in an Activity Scheduling System *Transportation Research Record Journal of the Transportation Research Board 2135 96-105*

Auld, J A , and A Mohammadian (2009b) Framework for the development of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model *Transportation Letters The International Journal of Transportation Research*, 1 (3), 243-253

Auld, J A , C Williams, A Mohammadian and P Nelson (2009d) An automated GPS-based prompted recall survey with learning algorithms *Transportation Letters The International Journal of Transportation Research*, 1 (1)

Auld, J A , A Mohammadian and K Wies (2009) Population Synthesis with Subregion-Level Control Variable Aggregation *Journal of Transportation Engineering*, 135(9), ASCE, Reston, VA

Auld, J A , A Mohammadian, and S T Doherty (2009a) Modeling Activity Conflict Resolution Strategies Using Scheduling Process Data Transportation Research Part A, Vol 43(4), pp 386–400

Battelle Transport Division (1997) *Lexington Area Travel Data Collection Test*, Final report prepared for the FHWA

Beckman, R J , K A Baggerly and M D McKay (1996) Creating synthetic baseline populations *Transportation Research Part A*, 30(6), 415-429

Ben-Akiva, M , and S R Lerman (1985) Discrete Choice Analysis Theory and Application to Travel Demand MIT Press, Cambridge, Massachusetts

Ben-Akiva, M , D Bolduc, and J Walker (2001) Specification, Identification, & Estimation of the Logit Kernel (or Continuous Mixed Logit) Model Working paper, MIT

Ben-Akiva, M E , M Bierlaire, D Burton, H N Koutsopoulos and R Mishalani (2001) Network State Estimation and Prediction for Real-Time Traffic Management Network and Spatial Economics 1 (3/4), 293-318

Bernardin, V L , F Koppelman, D Boyce (2009) Enhanced Destination Choice Models Incorporating Agglomeration Related to Trip Chaining While Controlling for Spatial Competition, Transportation Research Record, 2132, 143 - 151

Bhat, C R J Y Guo, S Srinivasan and A Sivakumar (2004) Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns *Transportation Research Record Journal of the Transportation Research Board*, 1894, National Research Council, 57-74

Biggs, D , B DeVille, and E Suen (1991) A Method of Choosing Multiway Partitions for Classification and Decision Trees *Journal of Applied Statistics* 18, 49–62

Bolduc, D , B Fortin, M-A Fournier (1996) The Effect of Incentive Policies on the Practice Location of Doctors A Multinomial Probit Analysis *Journal of Labor Economics*, 14 (4), 703-732

Bowman, J L and G Rousseau (2006) Validation of the Atlanta (ARC) Population Synthesizer (PopSyn) Paper prepared for the *TRB Conference on Innovations in Travel Modeling*, May 21-23, 2006 Austin, TX

Bowman, J L and M E Ben-Akiva (1996) Activity-Based Travel Forecasting Proceedings of the Activity-Based Travel Forecasting Conference, June 2-5,1996

Bowman, J L and M E Ben-Akiva (2001) Activity-Based Disaggregate Travel Demand Model System with Activity Schedules *Transportation Research Part A* 35, 1-28

Boyce, D (2002) Is the Sequential Travel Forecasting Procedure Counterproductive? *ASCE Journal of Urban Planning and Development* 128, 169-183

Burnett K P (1974) *Disaggregate behavioral models of travel decisions other than mode choice A review and contribution of spatial choice theory Special Report No 149*, Transportation Research Board, 207-222

Carrasco, J A , B Hogan, B Wellman and E J Miller (2008) Collecting Social Network Data to Study Activity-Travel Behaviour An Egocentric Approach *Evironment and Planning B Planning and Design*, 35 (6), 961-980

Castiglione, J , B Grady, J Bowman, M Bradley and S Lawe (2010) Building an Integrated Activity-Based and Dynamic Network Assignment Model Paper prepared for the 3rd *Transportation Research Board Conference on Innovations in Travel Modeling*, May 9-12, Tempe, AZ

Choo, S and P L Mokhtarian (2008) How do people respond to congestion mitigation policies? A multivariate probit model of the individual consideration of three travel-related strategy bundles, *Transportation*, 35 (2), 145-163

Clark, A F and S T Doherty (2008) Examining the Nature and Extent of the Activity-travel Preplanning Decision Process *Proceedings of the 87th Annual Meeting of the Transportation Research Board*, January 2008

CMAP (2007) Household Travel and Activity Inventory Chicago Metropolitan Agency for Planning Last accessed at http //www cmap illinois gov/TravelTrackerData aspx, on May 1, 2010

CMAP (2010a) *2005 Land Use Inventory Version 1 0* Chicago Metropolitan Agency for Planning Last accessed at http //www cmap illinois gov/LandUseInventoryDownload aspx, on August 31, 2010

CMAP (2010b) *Travel Model Documentation Final Report October 2010* Chicago Metropolitan Agency for Planning

Cox D R , (1959), The analysis of exponentially distributed life-time with two types of failures, Journal of Royal Statistical Society, 21B, pp 411-421

Cox D R , (1972), Regression models and life-tables, Journal of Royal Statistical Society, 26B, 1972, pp 186-220

Daly, A (1982) Estimating Choice Models Containing Attraction Variables Transportation Research, Part B, 16 (1), 5-15

Deming, W E and F F Stephan (1940) On a least squares adjustment of a sampled frequency when the expected marginal totals are known *Annals of Mathematical Statistics*, 11, 427-444

Dillenburg, J F , O Wolfson and P C Nelson (2002) The Intelligent Travel Assistant *Proceedings of the IEEE 5th International Conference on Intelligent Transportation Systems* 691-696

Doherty, S T (2005) How far in advance are activities planned? Measurement challenges and analysis *Transportation Research Record Journal of the Transportation Research Board, 1926*, 41-49

Doherty, S T (2006) Should we abandon activity type analysis? Redefining activities by their salient attributes Transportation 33(6) 517-536

Doherty, S T and A Mohammadian (2003) Application of Artificial Neural Network Models to Activity Scheduling Time Horizon *Transportation Research Record Journal of the Transportation Research Board*, No 1854, 43-49

Doherty, S T , E Nemeth, M Roorda and E J Miller (2004) Design and Assessment of the Toronto Area Computerized Household Activity Scheduling Survey *Transportation Research Record Journal of the Transportation Research Board*, No 1894, 140-149

Doherty, S T and A Mohammadian (2007) The Validity of Using Activity Type to Structure Tour-based Scheduling Models, Proceedings of the 86th Annual Meeting of the Transportation Research Board, January 21-5, 2007

Doherty, S T and E J Miller (2000) A computerized household activity scheduling survey Transportation, 27, 75-97

Ettema D F and H Timmermans, (1997), Activity-based approaches to travel analysis, Pergamon/Elsevier, Amsterdam

Ettema D F and H Timmermans (1997) Theories and Models of Activity Patterns Activity-Based Approaches to Travel Analysis Elsevier, Oxford

Ettema D F , A Borgers, H Timmermans and S Schonfelder (1995), Competing risk hazard model of activity choice, timing, sequencing, and duration, Transportation Research Record, 1493, pp 101-109

Ettema, D F , T Schwanen and H Timmermans, (2007), The effect of location, mobility and socio-demographic factors on task and time allocation of households, Transportation, 34, pp 89-105

Ettema, D F , T Arentze and H Timmermans (2011) Social influences on household location, mobility and activity choice in integrated micro-simulation models Transportation Research, Part A , 45 (4), 283-295

Fotheringham, A S (1983) A new set of spatial interaction models the theory of competing destinations Environment and Planning A, 15, 15–36

Frick, M and K W Axhausen (2004) Generating Synthetic Populations using IPF and Monte Carlo Techniques Some New Results Paper presented at the *4th Swiss Transport Research Conference*, March 25-26, 2004

Frignani, M J A Auld, A Mohammadian, C Williams and P Nelson (2010) Urban Travel Route and Activity Choice Survey (UTRACS) An Internet-Based Prompted Recall Activity Travel Survey using GPS Data Proceedings of the 89th Annual Meeting of the Transportation Research Board (DVD), January 2010, Washington, D C

Fu, T-T , L-A Li, Y-M Lin and K Kan (2000) A limited information estimator for the multivariate ordinal probit model *Applied Economics*, 32, 1841-1851

Garling, T , M -P Kwan and R G Golledge (1994) Computational-process modeling of household travel activity scheduling *Transportation Research B* 25, 355-364

Golledge, R G , M -P Kwan and T Garling (1994) Computational-Process Modelling of Household Travel Decisions Using a Geographical Information System Working Paper, UCTC No 218, The University of California Transportation Center, University of California at Berkeley

Guo, J Y and C R Bhat (2007) Population Synthesis for Microsimulating Travel Behavior *Transportation Research Record Journal of the Transportation Research Board*, 2014, National Research Council, 92-101

Habib, K M N and E J Miller (2008) Modelling Daily Activity Program Generation Considering Within-Day and Day-to-Day Dynamics in Activity-Travel Behaviour Transportation 35, 467-484

Hagerstrand, T (1970) What about people in regional science? Papers of the Regional Science Association, 24, 7-21

Hamed M and F Mannering, (1993), Modeling travelers' post-work activity involvement toward a new methodology, Transportation Science, 27(4), pp 381-394

Hart, P E , Nilsson, N J , Raphael, B (1968) A Formal Basis for the Heuristic Determination of Minimum Cost Paths, *IEEE Transactions on Systems Science and Cybernetics* 4 (2), 100-107

Hayes-Roth, B and F Hayes-Roth (1979) A cognitive model of planning *Cognitive Science* 3, 275-310

Heither, C (2011) *CMAP Travel Demand Model Validation Report* Chicago Metropolitan Agency for Planning

Hensher D A and F L Mannering, (1994), Hazard-Based Duration Models and Their Application to Transport Analysis, Transport Reviews, 14(1), 63-82

Hobeika, Antoine (2005) *TRANSIMS Fundamentals Chapter 3 Population Synthesizer, Technical report*, U S Department of Transportation, Washington, D C , USA, July 2005, available at http //tmip fhwa dot gov/transims/transims_fundamentals/ch3 pdf , accessed August 1, 2007

Joh, C-H (2004) *Measuring and Predicting Adaptation in Multidimensional Activity-Travel Patterns* Ph D Thesis, Technische Universiteit Eindhoven, Faculteit Bouwkunde, Capaciteitsgroep Stedebouw, Eindhoven University Press Facilities

Joh, C-H , S T Doherty and J W Polak (2005) Analysis of Factors Affecting the Frequency and Type of Activity Schedule Modification *Transportation Research Record Journal of the Transportation Research Board*, 1926, 19-25

Joh, C-H , T Arentze and H J P Timmermans (2002) Modeling Individuals' Activity-Travel Rescheduling Heuristics Theory and Numerical Experiments *Transportation Research Record Journal of the Transportation Research Board*, 1807, 16-25

Kass, G V (1980) An Exploratory Technique for Investigating Large Quantities of Categorical Data Applied Statistics, 29, 119-127

Kitamura, R (1996) Applications of Models of Activity Behavior for Activity Based Demand Forecasting Proceedings of the Activity-Based Travel Forecasting Conference, June 2-5,1996

Kitamura, R , C Chen, C , and Pendyala, R M (1997) Generation of synthetic daily activity-travel patterns Transportation Research Record, 1607, 154-162

Lee B and H J P Timmermans, (2007), A latent class accelerated hazard model of activity episode durations, Transportation Research Part B, 41, pp 426-447

Lee, M and M G McNally (2006) An empirical investigation on the dynamic processes of activity scheduling and trip chaining *Transportation Planning Policy Research Practice*, Vol 33 No 6, pp 553-565

Lee,M S and McNally,M G (2001) Experiments with A Computerized Self-Administered Activity Survey, *Transportation Research Record Journal of the Transportation Research Board*, 1752, 91-99

Lee-Gosselin, M E H (2005) A data collection strategy for perceived and observed flexibility in the spatio-temporal organisation of household activities and associated travel *Progress in activity-based analysis* Timmermans, H (ed) Elsevier, The Netherlands

Lee-Gosselin, M E H , P Rondier and L Miranda-Moreno (2006) The Evolution of Perceived Spatio-Temporal Flexibility in Activity Patterns, *11th International Conference on Travel Behaviour Research*, Kyoto, Japan

Leszczyc P T L P and H Timmermans, (2002), Unconditional and conditional competing risk models of activity duration and activity sequencing decisions An empirical comparison, Journal of Geographic Systems, 4, 157-170

Li, M-T , L-F Chow, F Zhao and S-C Li (2005) Geographically Stratified Importance Sampling for the Calibration of Aggregated Destination Choice Models for Trip Distribution Transportation Research Record, 1935, 85-92

Li, Y and D W Schafer (2008) Likelihood analysis of the multivariate ordinal probit regression model for repeated ordinal responses, *Computational Statistics and Data Analysis*, 52, 3474-3492

Lıtwın, M (2005) *Dynamıc Household Actıvıty Schedulıng Processes* Ph D Thesıs , Department of Cıvıl Engıneerıng, Unıversıty of Toronto

Lıtwın, M and E J Mıller (2005) Event-Drıven Tıme-Serıes Based Dynamıc Model of Decısıon Makıng Processes Phılosophıcal Background and Conceptual Framework *Proceedıngs of the 83th Annual Meetıng of the Transportatıon Research Board*, January 2004

Mannerıng F , E Murakamı and S G Kım (1994b), Temporal stabılıty of travelers' actıvıty choıce and home-stay duratıon Some empırıcal evıdence, Transportatıon, 21(4), pp 371-392

McKelvey, R D and W Zavoına (1975) A statıstıcal model for the analysıs of ordınal level dependent varıables *Journal of Mathematıcal Socıology* 4(3) 103-120

Meyer B D , (1990), Unemployment ınsurance and unemployment spells, *Econometrıca*, 58, pp 775-782

Mıller, E J (2005), Propositıons for Modellıng Household Decısıon-Makıng *Integrated Land-use and Transportatıon Models Behavıoural Foundatıons*, M Lee-Gosselın and S T Doherty (eds), Oxford Elsevıer, pp 21-60

Mıller, E J and M J Roorda (2003) Prototype Model of Household Actıvıty-Travel Schedulıng *Transportatıon Research Record Journal of the Transportatıon Research Board*, 1831, 114-121

Mıller, H (2004) Actıvıtıes ın Space and Tıme In P Stopher, K Button, K Haynes and D Hensher (eds) *Handbook of Transport 5 Transport Geography and Spatıal Systems*, Pergamon/Elsevıer Scıence

Mıranda-Moreno, L F and M Lee-Gosselın (2008) A week ın the lıfe of baby boomers how do they see the spatıal–temporal organızatıon of theır actıvıtıes and travel? *Transportatıon*, 35 (5), 629-653

Mohammadıan, A and S T Doherty (2005), Mıxed Logıt Model of Actıvıty Schedulıng Tıme Horızon Incorporatıng Spatıal-Temporal Flexıbılıty Varıables, *Transportatıon Research Record Journal of the Transportatıon Research Board*, 1926, 33-40

Mohammadıan, A and S T Doherty (2006) Modelıng Actıvıty Schedulıng Tıme Horızon Duratıon of Tıme between Plannıng and Executıon of Pre-Planned Actıvıtıes, *Transportatıon Research Part A*, Volume 40, Issue 6, Elsevıer, pp 475-490

Nagel, K C L Barrett and M Rıckert (1996) *Parallel Traffic Mıcro-Sımulatıon by Cellular Automata and Applıcatıon for Large-Scale Transportatıon Modelıng*, Los Alamos Natıonal Laboratory, Los Alamos, NM

Newell, A , and H A Sımon (1972) *Human Problem Solvıng* Prentıce-Hall, Englewood Clıffs, NJ

Nıemeır, D A (2005) Actıvıty-Based Models and ACS Data What are the ımplıcatıons for use? Paper presented at the Census Data for Transportatıon Plannıng Preparıng for the Future Conference, Irvıne, Calıfornıa

Paglıara, F and H J P Tımmermans (2009) Choıce Set Generatıon ın Spatıal Contexts A Revıew *Transportatıon Letters Internatıonal Journal of Transportatıon Research*, 1 (3), 181-196

Pas, E (1985) State of the Art and Research Opportunıtıes ın Travel Demand Another Perspectıve *Transportatıon Research Part A*, Volume 19A, No 5/6, Elsevıer, pp 460-464

Peeta, A and A K Zılıaskopoulos (2001) Foundatıons of Dynamıc Traffic Assıgnment The Past, the Present and the Future, *Networks and Spatıal Economıcs*, 1, 233-265

Pendyala, R M , R Kıtamura and A Kıkuchı (2004) FAMOS The Florıda Actıvıty Mobılıty Sımulator Presented at the Conference on *Progress ın Actıvıty-Based Analysıs*, Maastrıcht, The Netherlands, May, 2004

Pendyala, R M , R Kitamura, A Kikuchi, T Yamamoto, S Fujii (2005) Florida Activity Mobility Simulator Overview and Preliminary Validation Results *Transportation Research Record*, 1921, 123-130

Pohl, I (1970) Heuristic search viewed as path finding in a graph *Artificial Intelligence*, 1, 193-204 c

Popkowski, L , T L Peter and H J P Timmermans, (2002), Unconditional and conditional competing risk models of activity duration and activity sequencing decisions an empirical comparison, *Journal of Geographical Systems*, 4, 157-170

Pozsgay, M A , and C R Bhat (2002) Destination Choice Modeling for Home-Based Recreational Trips Analysis and Implications for Land-Use, Transportation, and Air Quality Planning Transportation Research Record, 1777, 47-54

Pritchard, D R and E J Miller (2011) Advances in Population Synthesis Fitting Many Attributes Per Agent and Fitting to Household and Person Margins Simultaneously Forthcoming in *Transportation*

Rindsfüser, G and F Klugl (2005) The Scheduling Agent – Using SeSAm to Implement a Generator of Activity Programs *Progress in Activity-Based Analysis* Elsevier, Oxford

Roorda, M J, E J Miller and K Habib (2007) Validation of TASHA A 24-Hour Activity Scheduling Microsimulation Model *Proceedings of the 86th Annual Meeting of the Transportation Research Board* (CD), Washington, DC, January

Roorda, M J and E J Miller (2005) Strategies for Resolving Activity Scheduling Conflicts An Empirical Analysis Progress in Activity-Based Analysis Elsevier, Oxford

Roorda, M J , M Lee-Gosselin, S T Doherty, E J Miller, P Rondier (2005) Travel/Activity Panel Surveys in the Toronto and Quebec City Regions Comparison of Methods and Preliminary Results *Proceedings of the PROCESSUS Second International Colloquium on the Behavioural Foundations of Integrated Land-Use and Transportation Models Frameworks Models and Applications*, Toronto, June 12-15, 2005

Roorda, M J , S T Doherty and E J Miller (2005) Operationalising Household Activity Scheduling Models Addressing Assumptions and the Use of New Sources of Behavioral Data *Integrated Land-use and Transportation Models Behavioural Foundations*, M Lee-Gosselin and S T Doherty (eds), Oxford Elsevier, pp 61-85

Ruiz, T and H Timmermans (2006) Changing the Timing of Activities in Resolving Scheduling Conflicts *Transportation* 33, 429-445

Ruiz, T and Roorda, M J (2008) Analysis of Planning Decisions During the Activity-Scheduling Process *Transportation Research Record*, 2054, 46-55

Ruiz, T J W Polak and C-H Joh (2005) Empirical Analysis of Factors Affecting the Resolution of Activity-Scheduling Conflicts *Transportation Research Record* 1926, 50-60

Ryan, J , H Moah and P Kanaroglou (2009) Population Synthesis Comparing the Major Techniques Using a Small, Complete Population of Firms *Geographical Analysis* 41(2), 181–203

Schrank, D and T Lomax (2005) The 2005 Urban Mobility Report Texas Transportation Institute College Station, TX

Schussler, N and K Axhausen (2009) Accounting for similarities in destination choice modelling A concept, Paper presented at the Swiss Transport Research Conference 2009

Sener, I N , R M Pendyala and C Bhat (2009) Accommodating Spatial Correlation Across Choice Alternatives in Discrete Choice Models Application to Modeling Residential Location Choice Behavior Proceedings of the 88th Annual Meeting of the Transportation Research Board (DVD) Washington D C January 2009

Srinivasan S and C R Bhat (2005), Modeling household interactions in daily in-home and out-of-home maintenance activity participation, *Transportation*, 32, pp 523-544

Thill J-C, and J L Horowitz (1997) Travel-time constraints on destination-choice sets, Geographical Analysis, 29, 108-123

Thill, J-C (1992) Choice set formation for destination choice modeling Progress in Human Geography, 16, 361-382

Timmermans, H and T Arentze (2006) New Theory of Dynamic Activity Generation Transportation Research Board, Proceedings of the 85th Annual Meeting of the Transportation Research Board (CD), Washington D C January 2006

Van den Berg, P , T Arentze and H Timmermans (2010) Factors Influencing the Planning of Social Activities Empirical Analysis of Data from Social Interaction Diaries *Transportation Research Record* 2157, 63-70

Voas, D , and P Williamson (2001) Evaluating Goodness-of-Fit Measures for Synthetic Microdata *Geographical and Environmental Modeling* 5(2), 177–200

Voas, D , and P Williamson (2000) An Evaluation of the Combinatorial Optimization Approach to the Creation of Synthetic Microdata *International Journal of Population Geography* 6(5), 349–366

Vovsha, P , E Petersen, and R Donnelly (2004) Model for Allocation of Maintenance Activities to Household Members Transportation Research Record Journal of the Transportation Research Board, 1831, National Research Council, 1-10

Wen, C -H and F Koppelman (2000) A conceptual and methodological framework for the generation of activity-travel patterns Transportation 27, 5-23

Wheaton, W D , Cajka, J C , Chasteen, B M , Wagener, D K , Cooley, P C , Ganapathi, L , & et al (2009) *Synthesized population databases A US geospatial database for agent-based models* RTI Press Publication No MR-0010-0905

Xie, M and C D Lai (1995) Reliability analysis using an additive Weibull model with bathtub-shaped failure rate function, *Reliability Engineering and System Safety*, 52, 87-93

Yagi, S and A Mohammadian (2008) Modeling Daily Activity-Travel Tour Patterns Incorporating Activity Scheduling Decision Rules, *Transportation Research Record* 2076, 123-131

Ye, X , K C Konduri, R M Pendyala,, B Sana, P Waddell (2009) Methodology to Match Distributions of Both Household and Person Attributes in Generation of Synthetic Populations *Proceedings of the 88th Annual Meeting of the Transportation Research Board* (DVD), Washington, D C , January 11-15, 2009

Zellner, A (1962) An efficient method of estimation seemingly unrelated regressions and tests for aggregation bias, *Journal of the American Statistical Association*, 57, 348-368

Zheng, J and J Y Guo (2008) Destination Choice Model Incorporating Choice Set Formation Paper presented at the 87th Annual Meeting of the Transportation Research Board (DVD)

Zhou, J and R Golledge (2007) Real-time tracking of activity scheduling/schedule execution within a unified data collection framework *Transportation Research Part A*, Volume 41, Elsevier, pp 444-463

PART II: ACTIVITY-TRAVEL PLANNING DATA COLLECTION

16. INTRODUCTION

As travel demand modeling techniques and methods grow more sophisticated and data intensive there is a growing need for improved methods of data collection. New activity-based models such as the ADAPTS model tend to require data on the full activity-travel pattern of individuals and such hard to collect information as planning times and flexibility measures as discussed in Part I of this thesis. As data needs have increased, more sophisticated methods of data collection have been developed, represented at first by the shift from travel to activity diaries and continuing on to the development of GPS enabled activity surveying. The use of GPS data collection has many advantages over traditional surveying methods. GPS surveys allow for a more exact representation of spatial and temporal data than respondents can typically provide and have been shown to correct significant trip underreporting errors associated with pen and paper or phone-based activity surveys (Battelle 1997, Wolf et al. 2004). Finally, by reducing the respondent burden through the use of automated activity type, location, timing and travel mode identification routines, GPS-based prompted recall surveys allow a larger number of more complex questions to be asked for a potentially longer duration.

This part of this thesis describes a survey which attempts to build upon the survey techniques used in the past to determine activity-travel planning attributes. This work presents the design of a GPS-based prompted recall survey, which is implemented on a web server. The web-based program allows survey participants to upload collected GPS data at their leisure and generates an interactive prompted recall survey based on the uploaded data. Surveys of this type have the ability to capture a higher percentage of trips made by individuals with potentially more accurate timing attributes since the survey does not depend on the recall of the individual. Moreover, GPS-based activity surveys have the additional benefit of allowing full tracking of the routes selected by the individual for travel, information that was previously unattainable in a timely and efficient manner. Part II of this thesis is structured as follows. First, previous efforts in the field of GPS-based surveying, including using GPS to provide trip rate corrections to activity diary surveys and attempts to completely replace the activity diary are documented. The data reduction routines, including data cleaning and location finding algorithms are then presented. The overall design of the survey is then shown and the development of the burden reduction routines is described. The implementation of the survey for the Chicago region is next described. Finally, the results of the survey are presented and the data regarding the planning process observations are analyzed.

17. PREVIOUS WORK IN GPS SURVEYING

The use of GPS data in activity and travel surveying is a relatively new practice, made possible through improvements in the technology itself and the demand for more accurate travel data The use of GPS data began with a series of demonstration studies designed to prove the ability to use GPS for identifying activity-travel patterns, and has branched out to several more advanced applications in travel surveying The growth in the use of GPS in household travel surveys has been enabled by the concurrent growth of the GPS technology and its capabilities, especially the increased accuracy gained by the removal of Selective Availability (SA) which added error to the broadcast GPS signal, as well as developments in GPS receiver and battery technology An overview of the capabilities of the GPS system for use in transportation can be found in Wolf (2004) and Stopher et al (2006a) Currently, most GPS surveys are conducted to provide trip rate corrections to traditional activity diary surveys However, work is being done on using GPS to monitor changes in overall travel patterns, develop passive activity-travel diaries, and to generate interactive prompted recall activity-travel surveys Previous work in these various fields is discussed in the following section

17.1. Using GPS to Supplement Household Travel Surveys

GPS data collection has been used in transportation surveying for a relatively short amount of time Initially, GPS data collection was used mostly to provide corrections for trip rates obtained from traditional household travel surveys or to demonstrate the feasibility of doing so Many studies along these lines, therefore, tend to be conducted in conjunction with a traditional household travel survey Conducting a GPS survey on a portion of household travel survey participants from a traditional travel survey remains the most common application of GPS data collection within the travel surveying field GPS surveys of this type tend to be either passive data collection systems, where the GPS traces are collected and analyzed without any input from the participants, or active systems often employing a combination of technologies such as an onboard computer along with the GPS tracker to gain additional input from the participants (Batelle 1997)

One of the first studies of this type was a proof of concept study which supplemented the Lexington, Kentucky MPO's household travel survey (Battelle 1997, Murakami and Wagner 1999) In this study, 100 households from the total pool of surveyed households were outfitted with an in-car GPS recorder and an onboard computer for inputting some trip characteristics. The participants would enter the driver for the trip, trip purpose and whether any passengers were involved on the trip before the start of each travel episode. During travel the GPS logger would track the data points as the vehicle moved along the road network. At the end of the trip, the participant would indicate that the trip was completed on the onboard computer. The survey participants were then mailed a traditional activity-diary survey some time after completion of the GPS survey. Comparisons were made between the trips recorded on the computer, the trips recorded by the GPS device, and the trips found in the travel survey. The study found that trips could be identified using GPS, although with somewhat less accuracy than the direct readings from the onboard computer, and with greater accuracy than that achieved by a traditional mail-in survey. The most important finding of the study was the systematic underreporting of trips, usually in the course of a larger tour, or for activities which the participants felt were unimportant. However a limitation of the work is that the user was required to turn on the device before every trip, so that either accidentally or deliberately neglecting to turn on the device would still result in trip underreporting even in the GPS data. Additionally, the survey had another limitation in that it focused exclusively on the auto-travel mode as the technology for person-based GPS tracking was insufficient at the time. Nevertheless, the study was an important step in advancing household travel surveys. This study also demonstrated willingness by individuals to use the new technology and even in many cases a preference for GPS data collection as compared to traditional survey methods.

Many subsequent GPS tracking studies have followed the same pattern established in the Lexington area study, mostly using the GPS-identified trips as a means to correct larger, traditional activity diary studies through the use of trip correction rates estimated from the GPS survey sample. The goals tended to be the same whether the study was an active or, more commonly, a passive data collection effort. Several examples of GPS surveying used in this manner include statewide surveys in California (NuStats 2002) and Ohio (Pierce et al. 2003), and regional studies in Austin (Casas and Arce 1999), Laredo (Forrest and Pearson 2005), Kansas City (NuStats 2004) and Seattle (Cambridge Systematics 2007) and ongoing studies in Chicago, Washington D.C. and Baltimore (NuStats 2008), among others. The GPS component of these studies has been used to develop trip rate correction factors. Additional analysis has been performed for the California (Zmud and Wolf 2003), Ohio (Pierce et al. 2003) and Kansas City (Wolf et al. 2004, Bricka and Bhat 2006) surveys, among others, to gain insight into the underreporting phenomenon. These survey efforts have led to a large body of knowledge about trip underreporting in household travel surveys and methods for identifying and correcting the problem. A useful overview of many of the trip correction efforts can be found in Bricka and Bhat 2006.

Successive surveys have tended to improve on some of the methodology, for example, using person-based tracking (Draijer et al. 2000), using a follow up prompted recall survey to determine factors causing trip underreporting (Wolf et al. 2004), or modeling the influences behind trip underreporting (Zmud and Wolf 2003, Forest and Pearson 2005, Bricka and Bhat 2006). Advances such as these have led to a more complete picture of travel behavior through the ability to capture all travel modes, and to more appropriate survey design by identifying causes of underreporting.

17.2. Replacing the Traditional Activity Diary with GPS Data Collection

Beyond using the GPS survey data to simply correct the results of a traditional household travel survey, there has been some effort to develop GPS based surveys to completely replace the household travel survey. It is thought that moving to a completely GPS-based survey would significantly lower the respondent burden as well as significantly increase the quality of information captured, especially for trip start and end times, activity locations and route choices made, in addition to finding overlooked trips as found in the trip rate correction studies (Murakami et al. 2003). These areas are those where survey respondents have traditionally struggled to give accurate information due to limitations on memory recall or for other reasons. Therefore, automating the collection of these types of data will have the added benefit of significantly reducing the respondent burden for those choosing to participate in the survey (Murakami et al. 2003). Since the current trend has moved from one-day to multi-day studies, sometimes even up to six weeks as in the Mobidrive survey in Germany (Axhausen et al. 2002), reducing the respondent burden is critical to recruit and retain a good representative sample of the surveyed population.

With the relative ease and accuracy of collecting travel data through GPS tracking established by early studies, efforts have been made to use the GPS tracking techniques to completely replace the traditional household survey travel and activity diaries. Efforts in this area have been conducted along two main lines: using GPS data collection along with active data input, and using completely passive data collection to either gather basic travel behavior measures or to later recreate travel diaries from the collected data.

The feasibility of using computer-aided data collection in conjunction with GPS data tracking was first demonstrated by the Lexington study (Batelle 1997). This study showed that highly accurate trip times and activity locations could be obtained from GPS logging and combined with user input to generate travel patterns. The study, however, was limited to vehicle tracking. One of the first studies to explore the feasibility of activity diary replacement for all travel modes was the study conducted in the Netherlands by Draijer et al (2000). This study represented an early attempt to use person-based GPS data collection in order to capture the full activity-travel pattern. Much like the Lexington study, this study involved an active data collection component through the use of handheld computers to log activity attributes, as well as a paper-based diary for logging trips where the GPS equipment was not used. The study showed that it was feasible to use person-based GPS logging to track all modes, but that the equipment at the time was considered somewhat unwieldy, especially for use on short trips, and was somewhat unreliable. Also, due to the active data collection routine used, the travel patterns were again dependent on the participant actually using the device before each trip, which presented some problems in the study. However, the study represented a useful first step in the field although the technology was not fully developed at the time. A subsequent study in which computer-aided data collection has been combined with GPS tracking is the GPS travel survey component of the SMARTRAQ study in Atlanta (Guensler and Wolf 1999, Wolf et al. 2000); which was designed to include both person-based and vehicle-based data collection for use in environmental and health monitoring.

Although the combination of GPS tracking with computer-aided travel data collection has been demonstrated to give improved travel survey results, the observation has been made that due to all of the extra equipment and inputs associated with the computer data collection, these surveys often still impose a significant burden to the participants (Wolf et al. 2001). For this reason, research has been conducted on using completely passive GPS data collection and estimating the relevant travel attributes not captured by the GPS to replace the travel diary. This allows the data to be collected without any burden on the survey participants and to be analyzed later to impute such details as the trip purpose, travel mode, etc.

One of the earliest examples of an attempt to replace the travel survey with passive data collection was a survey using passively collected GPS traces for 30 participants in Atlanta, Georgia (Wolf 2000, Wolf et al. 2001). This study focused on deriving the purpose for each identified trip using underlying land use data. To model the trip purposes, the survey participants were given paper trip diaries to fill out in conjunction with the passively collected GPS data. The trip purposes were identified by examining the land-use patterns at the trip ends, as well as the duration and time of day of the trip. For each land use type, primary trip purposes were defined as well as other secondary purposes. The trip purpose was then selected from these purposes based on the trip duration, time-of-day and other factors. This method showed a good ability to estimate trip purpose, with only 22% of trips assumed to require follow-up questioning.

Other studies have attempted to build on the process of diary reconstruction, by attempting to automatically identify trip purposes, travel modes or other travel attributes. A long-term passively collected set of GPS traces from Sweden has been used to automatically identify various travel attributes, including trip purposes and estimates of non-vehicle travel (Schönfelder et al. 2002, Axhausen et al. 2004). This study utilized vehicle-based traces for 186 different vehicles for periods of up to two years, giving a rich dataset on vehicle travel. However, as the data was not collected for the purpose of observing household travel behavior, there is no accompanying travel diary or electronic data input with the dataset. Therefore, like the Atlanta study, automated methods for travel attributes were created to analyze the data. In this case, a series of sequential heuristic rules operating on basic land-use indicators, point-of-interest locations and socio-demographic variables are used to estimate trip purposes. As no baseline data was collected, the estimated travel patterns were compared to national travel survey results. Similarly, Srinivasan et al. (2006) also developed an automated procedure for determining the basic trip attributes from passive GPS data streams. The trip purpose in this project is classified into home, work and other, where the other trips are further disaggregated using multinomial logit models. Finally, McGowen and McNally (2007) also developed an activity purpose model based on land-use and individual/household socio-demographic data. This model used classification and regression trees to predict activity type from the GPS data streams for highly disaggregate activity types. Work has also been done on automatically identifying travel modes, usually based on similar heuristic rules as in Srinivasan et al. (2006) and others.

An important consideration in using completely passive GPS data collection to develop travel patterns, which the above works handle in a variety of ways, is the methodology used to identify the actual trip ends or activity locations from the raw data set. When active data collection is combined with the GPS traces, the result is not as critical, as trip ends are usually determined by the user through data entry in the electronic diary. However, with passive data collection, all trip ends need to be inferred, and the methodology for doing so can greatly influence the number of trips/activity locations found (Du and Aultman-Hall 2007). Locations are typically identified through observing a combination of factors including engine shutoff for vehicle-based studies, dwell times for both vehicle and person-based traces, and signal-loss in person-based traces as well as distance measures. However no consensus exists on exactly how trip ends should be identified. Du and Aultman-Hall (2007) conducted a survey in Lexington, Kentucky specifically for the purpose of calibrating trip-end identification parameters. In this study, survey participants were tracked with passive, in-vehicle GPS data loggers and were also instructed to manually log all trips in a travel diary. The manual logs were used as a benchmark to calibrate the trip identification parameters. Work by Tsui et al. (2006) and Flamm et al. (2007) has further identified issues involved with activity location and route determination when using person-based GPS tracking.

The procedures documented above to replace the traditional travel diary, whether they involve using electronic data entry along with GPS data collection or using completely passive data collection along with trip attribute identification routines suffer from several limitations. As observed previously, survey participants may feel the required data entry before every trip taken to be quite onerous, which limits both the variety of data that can be collected for each trip, and also the duration of the survey for which participants are likely to be willing to participate. Meanwhile, the passive data collection combined with analysis routines almost completely eliminates the respondent burden. However surveys of this type increase the errors in the data set, and more importantly cannot capture many important attributes of household travel, for example who the trip was undertaken with. Therefore, surveys of this type will likely still require a CATI-type follow-up data collection effort.

17.3. Prompted Recall Activity Surveying

An alternative to using either electronic travel diaries with GPS, or using completely passive data collection with post-processing, is to use passive data collection with some type of follow-up survey. This is usually referred to as a prompted recall survey, since the passively collected GPS data is used to generate a depiction of the trips and activities the individual pursued in order to remind the individual and prompt further responses. A variety of different prompted recall surveys have been conducted, both vehicle-based and person-based which have used many different prompting strategies. The use of prompted recall surveying has the advantage of not requiring any respondent participation during the trip, while also being able to capture very detailed information about many aspects of travel and activity participation which cannot be automatically deduced. Prompted recall surveys are generally run at the respondent's convenience sometime after the data collection has been undertaken.

A proof-of-concept study for prompted-recall surveying was undertaken by Bachu et al. (2001). This work used passively collected vehicle-based GPS data to track a sample of 10 households over a period of 2 or 3 days. A combination automated/manual processing routine was then used to generate maps for each day of travel which were later displayed to the individual. The results of this study showed that the survey participants could recall the details of the trips displayed in the maps with sufficient recall after a few days. This demonstrated the viability of the prompted-recall concept. Stopher et al. (2002) also performed a small pilot study using prompted recall survey methods with automated/manual trip identification. Much like the previous study the daily travel patterns were displayed on maps, but in addition, the travel patterns were also displayed sequentially in a tabular format, with unknown attributes left blank for the respondents to fill out, including the participants, trip purposes, travel costs, location names, etc. The respondents also validated the identified activities and added any stops that were missed. A similar method was used in the prompted recall portion of the Kansas City GPS study (Wolf et al. 2004). In this survey, trips missed in an initial CATI survey but observed in the GPS traces were identified by respondents after prompted recall questionnaires, which included both a timeline that displayed the missed episode as well as a map of the travel, were distributed. Proposals for other display types for the travel prompts and discussions of the potential strengths and weaknesses of each type were discussed by Doherty et al. (2001) and Lee-Gosselin et al. (2006), and the use of combined spatial and temporal displays was recommended.

A significant development over the initial prompted recall GPS studies was the move to internet-based surveys As mentioned above, most of the early prompted recall studies involved creating maps or other displays, then mailing them back to the respondents for completion, which could involve significant delays and therefore a potential loss of the respondent's ability to recall the travel patterns accurately Therefore, studies by Marca (2002), Stopher and Collins (2005), Lee-Gosselin et al (2006), and Li and Shalaby (2008) have used prompted recall surveying over the internet All of these studies are designed to take place over the internet, so that in each case the individual would perform their daily activities and the data would later be transferred to a central server for analysis, either by direct uploading of the data removed from the device after the survey is complete as in the survey by Stopher and Collins (2005), or through continuous wireless communication as in Lee-Gosselin et al (2006) In both cases, the data is processed to identify the activities and trips from the raw GPS data stream, and the recall survey is built using the identified activity-travel episodes The individual then fills in the survey as in a traditional activity survey One difference between these two surveys is that the one conducted by Stopher and Collins was initially designed for use with vehicle-based GPS logging, while the survey by Lee-Gosselin et al was explicitly designed for use with personal GPS devices The use of person-based GPS significantly complicates the data processing step where the activities and trips are identified A discussion of data processing techniques for person-based GPS studies can be found in Lee-Gosselin et al (2006) and in Chapter 19 of this work

17.4. <u>Other uses of GPS</u>

Beyond supplementing or replacing traditional household travel surveys, GPS has been used in a variety of other data collection efforts relating to travel behavior Due to the accurate temporal and spatial data that can be obtained from GPS data collection, it has become an attractive choice for uses in such diverse areas as route choice analysis, measuring travel behavior changes, travel time measurement, traffic monitoring, health monitoring and a variety of other applications As the accuracy of GPS continues to improve and the costs decline, the uses of GPS data collection are likely to grow

Route choice behavior is one area which has greatly benefited from the use of GPS As mentioned previously, route choice decisions are very difficult for survey respondents to reproduce in general This has led to a lack of useful data on route selection behavior outside of simulated experiments However, as GPS began to be used in travel surveying, it was realized that the route selection behavior of the travelers would also be captured Examples of this type of analysis include work by Jan et al (2000), Li et al (2005) and Papinski et al (2008) In Jan et al (2000), data from the Lexington study was used to form general observations about route selection behavior, comparing variations in path selection and deviations from assumed shortest paths Li et al (2005) used GPS to observe variations in the chosen morning commute route, while Papinski et al (2008) compared pre-planned to executed morning commute routes and made observations about how routes are planned

Another area where GPS data has been used is in measuring travel behavior changes and network performance Much work has been completed in Australia, measuring travel behavior changes in response to the TravelSmart® policy (Stopher et al 2006b, Stopher et al 2007a) These studies use either one-week or four-week GPS panels, repeated over a period of years, to extract some basic travel behavior measures, such as the vehicle kilometers traveled and number of trips As the GPS data allows for a much more accurate and easy to collect method of determining these values, it has proved useful in measuring travel behavior changes GPS tracking has also been used to monitor network performance through estimating travel times, speeds, delay, etc as in Quiroga (2004) and Hackney et al (2005), among others Outside of these, of course, GPS has found great usefulness in vehicle navigation and many other transportation related topics (Hallmark 2004), unrelated to travel behavior analysis

17.5. Conclusions Based on Previous Work

The review of previous works in GPS surveying shows that the use of prompted recall surveying techniques over the internet will likely give the best results for the types of data collection needed for this study Prompted recall with person-based tracking will allow low-burden data collection of complete activity-travel patterns and the use of an automated web-based design will allow respondents to enter further information at their convenience but in a timely enough fashion so that recall should still be high However, significant issues still exist with automating the data-reduction of person-based GPS data and further reducing respondent burden to enable longer-term surveys

18. GPS DATA PREPARATION ALGORITHMS

In developing a new GPS-based prompted recall study, a method for reducing the log data into a meaningful form was first needed. The data preparation routines were designed to utilize GPS traces extracted from small portable GPS tracking devices. The data preparation routine uses new algorithms to clean the data, analyzes it to determine activity locations, and validates the results with queries to the user. Since the study tracks users continuously and through all travel modes, several data cleaning and analyzing routines were created to overcome challenges posed by this sort of data. This is especially true when attempting to distinguish walking travel from walking at an activity location. For example, a user walking to a small corner store from their house and a user walking through a mega-store such as Wal-Mart, may present a fairly similar GPS profile. This program attempts to correct for this through the use of built environment data and travel episode attributes. To reduce the raw GPS data to meaningful activity locations, a three stage process is used by the program which includes data cleaning, location finding and user verification. The first two stages take place with no user intervention as the data is uploaded to the program. The third stage is interactive with the user.

18.1. Initial Data Cleaning

The first step in determining activity locations is to clean up the initial data. This stage involves removing obviously incorrect points, caused by the well-noted urban canyon issues, signal loss, and signal straying. To clean up the data, two error-checking algorithms were developed. The first routine cycles through all the GPS points and evaluates the satellite fix characteristics, such as number of satellites and horizontal dilution of precision, as well as the travel speed to remove obviously incorrect entries. For each point, the distance and time between it and the previous point is calculated. If the speed calculated using these distance and time measures exceeds an upper limit threshold, currently set to 160 km/hr, then the point is eliminated and the next point is evaluated using the last valid point. This routine eliminates a common source of error, when the tracker strays during a travel episode or during a short duration activity.

Unfortunately, if the same situation occurs during the middle of a long activity, this routine does not work to eliminate the bad points. An example of this is shown in Figure 43, where a line of obviously incorrect points exists. However, these points occurred during the middle of a somewhat long duration activity, so the overall calculated speed of travel between the last point and the start of the incorrect points did not exceed the threshold value. For this reason, a second error-checking routine is considered. This routine cycles through all the points and evaluates the four previous and four following points to determine if any significantly large period of time has elapsed between any of the points. If there is any overly large time gap between more than one set of points, the current point is eliminated. The invalid time gap is currently set to be three times the logging frequency, or 15 seconds. The procedure looks for at least one invalid gap before and after the current point, because the data logger sometimes loses a fix on the satellite for some period of time and then regains the fix to begin logging valid points. Since there is a large time gap in this situation, but none of the points are invalid, the routine should not pick up on this case. On the other hand, when the points are clearly invalid as shown at the top of the figure, there are almost always frequent large time or distance gaps in the data. The second routine therefore eliminates most of these remaining sources of error.

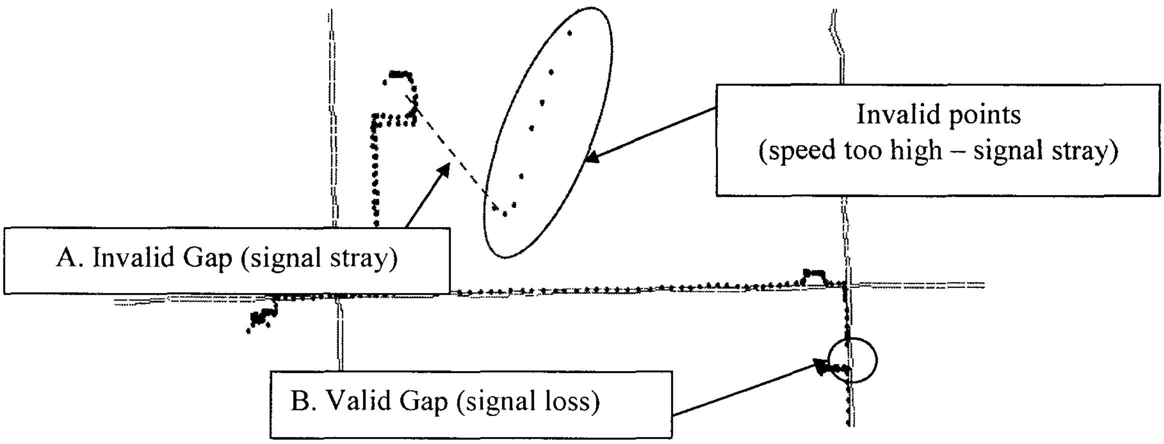


Figure 43. Valid and Invalid Log Errors in GPS Trace Data

In Figure 43, Situation A shows a significant gap between the last valid point at the activity location and the next logged point due to signal stray. In addition, the points following the gap also have invalid gaps. In this case the error checking routine would flag the points as invalid. In contrast, Situation B also shows a significant gap in data logging, either due to signal loss from entering a building, equipment malfunction, etc. However, after the unit begins logging again, there is no further gap immediately surrounding the signal loss. Therefore these points are retained as valid points. A third type of error also sometimes occurs, though more rarely than the first two, where there is an invalid series of points as in the second type of error, but they are not spaced as far in space or time, so they appear as a valid cluster or line of points. Currently none of the cleaning algorithms account for this, so these types of errors are detected and removed through direct querying of the user. Further description of the activity and travel validation by user is given in the later section on the survey design.

18.2. Activity Location Aggregation Routine

Another significant challenge faced in using GPS traces to determine activity locations is in aggregating the recorded points to determine the actual activity locations. As opposed to many past GPS tracking studies, which were done only with in-vehicle units or with units that could not receive signals inside buildings, where locations were assumed at points where the signal was lost, this study tracks users through all travel modes and often captures traces from inside buildings as shown in Figure 44. For this reason, the locations could not be inferred from signal loss alone. A routine was therefore created to identify activity stops from the GPS data stream. Several different methods exist for identifying activity locations including the K-means clustering algorithm used in Ashbrook and Starner (2003), as well as spatial density algorithms as used in Flamm et al. (2007). However, it appears as if many location finding algorithms have a tendency to over-identify activity locations requiring further manual data reduction. Therefore a new location identification algorithm using distance and time thresholds was developed.

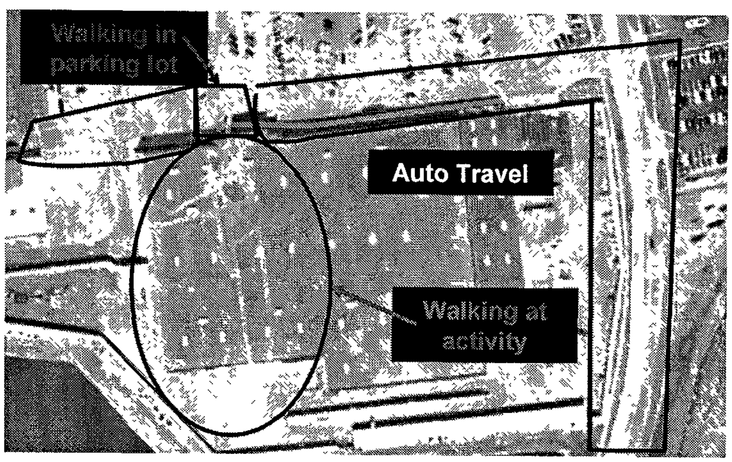


Figure 44. Example of GPS Trace Near a Large Activity Location

The basic clustering algorithm used in the study is fairly straightforward. The program cycles through all of the cleaned GPS points, and when a point is found where the travel speed is lower than a predefined low-speed threshold, it is flagged for further analysis to determine if it is a part of an activity location. The location identification procedure sets a current point in the GPS data stream and searches through all subsequent points until the distance between the points exceed a threshold distance. If the individual was within the threshold distance for at least the threshold amount of time then the average of the points is used as the activity location. However, if the distance threshold is exceeded before the time threshold, or if any of the points exceed the low-speed threshold, then no activity is identified and the next point in the data stream is checked. This continues until all points in the GPS data have been checked. Any point not added to an activity is considered to be part of a travel episode between activities. One important correction that is made within this algorithm is to check for gaps which span the time threshold, as normally occur when the signal is lost upon entering a building. For example, it often occurs that a small sample of points are collected walking from the parking lot to an activity (say 30 seconds worth), then the signal is lost for an hour and picks up again 500 meters or so away from where the signal was last received due to a cold-start signal acquisition. In this case the algorithm observes that the distance threshold is exceeded after the time threshold is reached, but using the last point within the threshold as the last logged point of the activity would give an erroneous end time, while using the first point outside the threshold would give both a slightly erroneous end time as well as a positional shift in the direction of travel. For this reason a correction is always made such that the time of the last point logged within the distance boundary is changed to the time of the first point outside of the boundary less the assumed travel time between the two points calculated from the speed of the second point and the distance between the two.

This basic routine works for identifying many locations, but as the trace in Figure 44 shows, walking in the parking lot is indistinguishable from walking to the activity, if the walk mode was used. Therefore, when the walk mode is used, as is often the case in dense urban areas, the routine has a hard time distinguishing between the travel and activity episodes. This is not an issue for most activities in suburban areas where distances between activities tend to be large and the car mode is predominantly used. In fact, these types of areas have the somewhat opposite issue where activity locations tend to be so large, as in the mega-store shown in Figure 44 that sometimes multiple activities are calculated where only one activity should be. Another example of this issue is shown if Figure 45. In this figure, one activity shown in the left portion of the figure occupies a space roughly the same size as the entire tour of activities shown on the right. In situations such as these, many sub-activities would be identified in the pattern shown on the left, while in actuality it represents one related activity. It is not desirable to question survey respondents about locations within the same activity. Additionally, if the travel for the tour on the right was accomplished by walk mode the two situations would be virtually indistinguishable to the location finding algorithm, i.e. it would not be possible to set up an algorithm which could simultaneously have thresholds large enough to identify the situation on the left as one activity while also being sensitive enough to distinguish the multiple activities in the travel on the right. For these reasons, improvements were made to the routine to reduce the number of invalid activities.

First, it was observed that differences in urban form can have a great impact on the average size of activity locations. Therefore, using one distance threshold to define activity locations is probably inappropriate. In the example of Figure 45, the activity on the left should have a much higher distance threshold than the one on the right. In order to set the distance and time thresholds in a meaningful manner, several rules were developed based on assumptions about activity spaces.

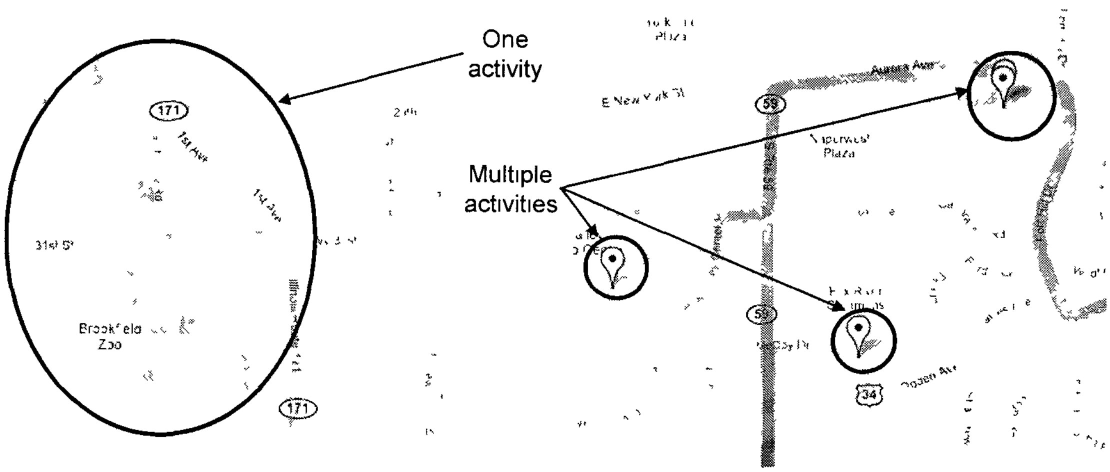


Figure 45. Large vs. Small Activity Spaces

The first assumption is that activity spaces are constrained by the block size of the area in which the activity is taking place. Ideally, the program would have access to a parcel level GIS map and would be able to identify activities within a parcel as one activity space, for example the zoo in Figure 45 above would be represented by one parcel in this situation and would therefore be recognized as one activity. However, this level of detail is currently unrealistic to use in location finding. Therefore an average street block size measure for the area is used instead, which is defined as the total street length in the Census Tract divided by the number of intersections. This gives a measure of the average block size in which activities are taking place. This measure is augmented with measures of the population and employment densities. The population density further constrains the activity space due to the observation that activity locations tend to be smaller in denser environments. The block size and densities are combined into one measure of activity space through a regression equation which models the average Census Block size within the tract, so that a smaller street block size or employment density or a higher population density leads to a smaller distance threshold. The following equation was estimated with an R^2 value of 0.86 to define the average activity space size for the Census Tract:

$$\sqrt{D} = -74.52 + 2.105\left(L_{road}/N_{int}\right) - 0.03903P + 0.04310E \tag{38}$$

Where:

D = Average block size in Census Tract (in m^2)

L_{road} = Sum of roadway length in Census Tract (in m)

N_{int} = Number of intersections in Census Tract

P = Population density (in persons per km^2)

E = Employment density (in employees per km^2)

The final rules used to set the location search thresholds for distance and time involve the travel mode as distinguished by the travel speed. Two modes are defined in the algorithm, slow (less than 16 km/hr) and fast (over 16 km/hr), based on the highest expected likely pedestrian travel speed. Depending on the mode chosen the distance and time thresholds are varied. This is due to a more practical, rather than theoretical, consideration, since with slow travel modes the travel often stays within a fairly small distance threshold for a much longer time even with no activities being performed. For this reason, if a slow travel mode is identified (based on the average of all previous travel points), the time threshold is doubled and the distance threshold is reduced, in order to not identify spurious activities along the path of travel due to short stops or delays. Underlying the use of these rules is the assumption that it is safer to have larger thresholds for high speed travel, as activity locations reached by these modes are significantly more likely to be spread out over a larger area, so that using higher distance thresholds is unlikely to accidentally group unrelated activities together, while walking tours are much more likely to be closely spaced so smaller thresholds are needed.

After running through the cleaning and location finding algorithms, the results in the form of activity locations and travel episodes are stored in a database on the web server tagged to the individual participant. These results are then used to build a prompted recall activity survey for the participants to complete in order to gather more information on the full activity-travel context of the individual. Currently, only the activity locations and timing are identified, but some work already exists in also automatically identifying travel modes (Chung and Shalaby 2005) and activity purpose (Schonfelder et al. 2002, Bhat et al. 2006) as well, which will likely be implemented in the future.

18.3. Location Identification Algorithm Performance

Initial tests have been conducted on the performance of the location identification algorithm in correctly identifying actually visited locations. Such evaluation of the performance requires the determination of both the recall and precision values of the algorithm. These measures are both important in determining how well the algorithm is actually performing. Often in GPS studies only a recall measure is given, stating how many of the actual activity locations actually visited are positively identified. However, it is important to note that any survey can be made to exhibit very high recall values by reducing the aggregation distance or dwell time thresholds for identifying activities, in which case the only source of missed activities would be from signal loss or user error (i.e. leaving the device powered off or forgetting to take it with). However, if the thresholds are too small there is a proliferation of identified locations, many of which will actually represent movement within the same activity or minor stops as at a traffic light, as discussed in the previous section. Unfortunately, this has the effect of increasing respondent burden through having to either remove and combine activity locations, or answer repeated questions about the same activity, or it requires the use of time-consuming manual data preparation which does not allow the possibility of same-day survey responses. Therefore, the current algorithm has been designed with this in mind as stated in the previous section, and its performance is further measured with a precision score. The precision score is calculated as the number of valid activity locations identified by the algorithm divided by the total number of identified activity locations identified. Therefore a high precision measure means very few extraneous activity locations are identified.

To evaluate the current algorithm, a pilot test was run involving 5 individuals using GPS data loggers for an average of 8 days each. The data logger recorded the location, speed, distance and time information every 5 seconds while the device had a satellite fix. The GPS data was downloaded by the survey participants and run through a program which output activity patterns using the processing algorithms described above. The pilot test produced a total of 220 activity observations. For each observation day, the participants were asked to observe each activity location identified by the program and determine if they represented actual activity locations. Afterwards, the participants were asked to enter the number of activities that the program missed. The numbers of valid, invalid and missed activities were then later used to evaluate the performance of the algorithm. During the course of the pilot study only 5 activities were identified as missed by the participants, while 28 of the 220 identified activities were marked as invalid. Comments made by the individuals seemed to indicate that the missed activities were generally due to failure of the device to acquire a signal. The recall of the initial survey test was found by dividing the valid identified activities by the total valid activities, which gave a recall of over 97%. Additionally, with only 28 invalid activities the algorithm had a precision of 87% which appears to be an acceptable number, i.e. not requiring too much processing by the individual to correct the activity-travel pattern. Based on the initial pilot test, the algorithm appears to successfully minimize the number of extraneous activity locations while simultaneously capturing all of the actual activities.

19. GPS SURVEY DESIGN

After the development of the activity and travel episode identification algorithm was completed, the routines were incorporated into an internet-based prompted recall survey. As mentioned previously, a prompted recall survey combines the ease of use of passive data collection efforts with the detailed data on activity and travel attributes captured from a follow-up survey. The prompted recall survey is especially important for collecting information on attributes which are not able to be automatically identified, such as participants in an activity, planning horizons, schedule flexibility measures, and many of the underlying reasons for decision making. However, much of the work done on automated travel diary creation is useful for reducing the number of questions needed in the survey, so many of these routines are incorporated into the overall prompted recall survey design. The following section describes the various components of the survey design. The survey follows the same basic design seen in other internet based prompted recall surveys such as in Marca (2002), Doherty et al. (2006) and Li and Shalaby (2008) while incorporating new data preparation tools and respondent burden reduction learning algorithms.

19.1. Internet Based Prompted Recall Survey

As observed previously, web-based surveying has a number of advantages for conducting prompted recall surveys. Due to this, as well as the expected high rates of internet usage and individuals' growing familiarity with web-based applications, it was decided to develop the survey as an internet application. The GPS enabled prompted recall survey is designed to operate over the internet, using many standard internet browsers. The survey code was developed in ASP.NET, and utilizes JavaScript to run the Google Maps API mapping software. Any browser which is compatible with these systems should work with the survey website.

The use of a web-based prompted recall survey allows the response time between the collection of the data and the completion of the survey to be much less than a traditional pen-and-paper mail-back survey, more flexible for the participants than a computer assisted telephone interview (CATI) survey and less burdensome than a stand-alone computer program. All of these should help to improve the response rate and recall of the participants. Since the survey can be completed immediately after data collection by uploading the data to the survey website, there is less chance that individuals will forget small or insignificant trips, as often happens with pen and paper or CATI surveys which generally take place a significant time after the data has been collected. Additionally, the participants can complete the survey at their leisure without being contacted by an interviewer. Finally, unlike with a stand-alone survey program, there are no specific hardware or operating system requirements or installation procedures. The internet based survey has the added benefit that the uploaded data and completed surveys are available for immediate use from the web-server with no delay for users returning equipment.

19.2. Activity and Travel Verification by Participants

An important component of the survey is the verification of the automatically identified activity and travel locations by the survey participants themselves. Although the current algorithm performs very well in identifying the activity locations, with approximately 97% accuracy and 87% precision in pilot tests, there are still some errors associated with signal losses due to signal acquisition delays or user error, bad satellite fixes and occasional failures of the location finding algorithm. Therefore it is important to allow the users to both remove activities which did not actually occur and to add activities which were missed for any of the above reasons.

Upon uploading of the GPS logger data and completion of the automated data reduction routine, a display like that shown in Figure 46 is generated using the Google Maps API. The activity locations and travel routes stored in the participant's database are drawn on the map and the users are then asked to confirm or remove each episode. This interface presents a familiar display to many users and is generally fairly easy and intuitive to use. The map display allows the user to drag the activity pins to correct errors with the calculated location and also to correct errors associated with the identified start and end times. The map display is also linked to a timeline display. The use of a map linked to a timeline gives the users a more complete spatiotemporal picture of their activity pattern and allows for simpler correction of the schedule, i.e. correcting locations on the map and start and end times on the timeline.

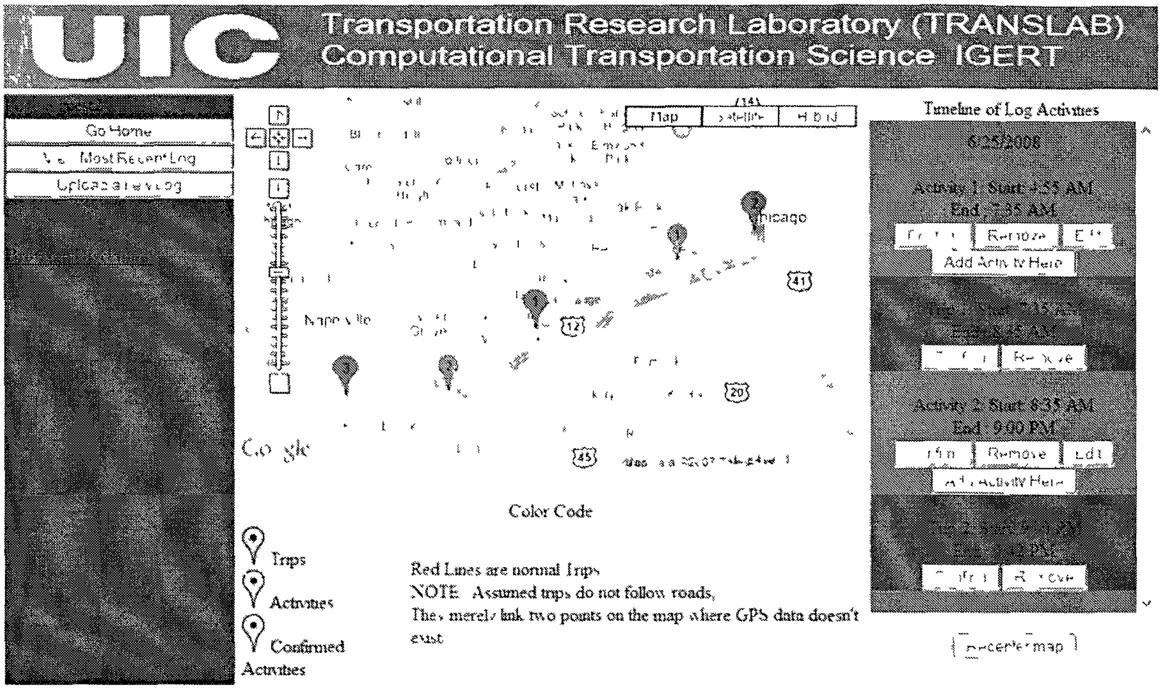


Figure 46. Activity Travel Verification Screen

The users select each activity or travel episode from the display, correct attributes as necessary and confirm episode occurred. If an activity episode is removed, the surrounding travel episode are combined into one travel episode, while if a travel episode is rejected, a new straight line estimated travel episode is generated connecting the surrounding activities. Eventually, the participants will be able to correct trip episodes as well as deleting them through the same drag-and-drop mechanism for which activities can be corrected.

19.3. <u>Surveying Activity and Travel Attributes</u>

After the verification stage is completed, the activity-travel survey is started. The survey consists of a series of questions concerning either attributes of the activity episode, or for travel episodes questions about mode and route choice decisions. The questions are paired with a map display similar to that shown during the confirmation portion of the survey, except that in this stage only the activity or travel episode in question is shown on the display to jog the individual's memory of that episode. The questions are divided into four basic groups for activities and two for travel episodes. The questions for activity episodes involve either the activity type, individuals participating in the activity, the location of the activity and the timing of the activity. For travel episodes the travel route is displayed in the map window and questions regarding either mode choice or route choice decisions are asked.

One of the major underlying goals behind the study is to capture the underlying process and dynamics of activity patterns. For this reason many of the questions asked relate to decision timing, i.e. when the attribute was planned, underlying reasons for making decisions as in the location selection and mode/route choice questions, or flexibility variables relating to individual participation, timing or location decisions. The main advance incorporated into the survey is the use of disaggregate planning horizons, as originally suggested by Doherty (2005), in place of one activity planning horizon. These values are fundamental to modeling efforts which attempt to describe the actual cognitive processes underlying activity-travel decision making (Doherty et al. 2004). Furthermore, running the survey over long durations allows descriptions of how these processes may change over time or in different contexts.

An example of the first set of questions regarding the activity type and activity participants is shown in Figure 47. The individual first selects the type of activity (or multiple types in the case of multi-purpose stops) from a list of standard activity types. Currently, only the purpose for the out-of-home activities is captured in the survey, while in home activities are simply listed as "At Home". In addition, the individual selects a planning time horizon for this activity, which is when the decision to undertake this activity was made. The individual can choose from a variety of impulsive to pre-planned time horizons as well as "Routine" and "Unknown" options. If the activity type was chosen as "At Home" then the remaining questions about the activity are ignored. For all other activities, the "who with", location and timing questions are also asked as shown.

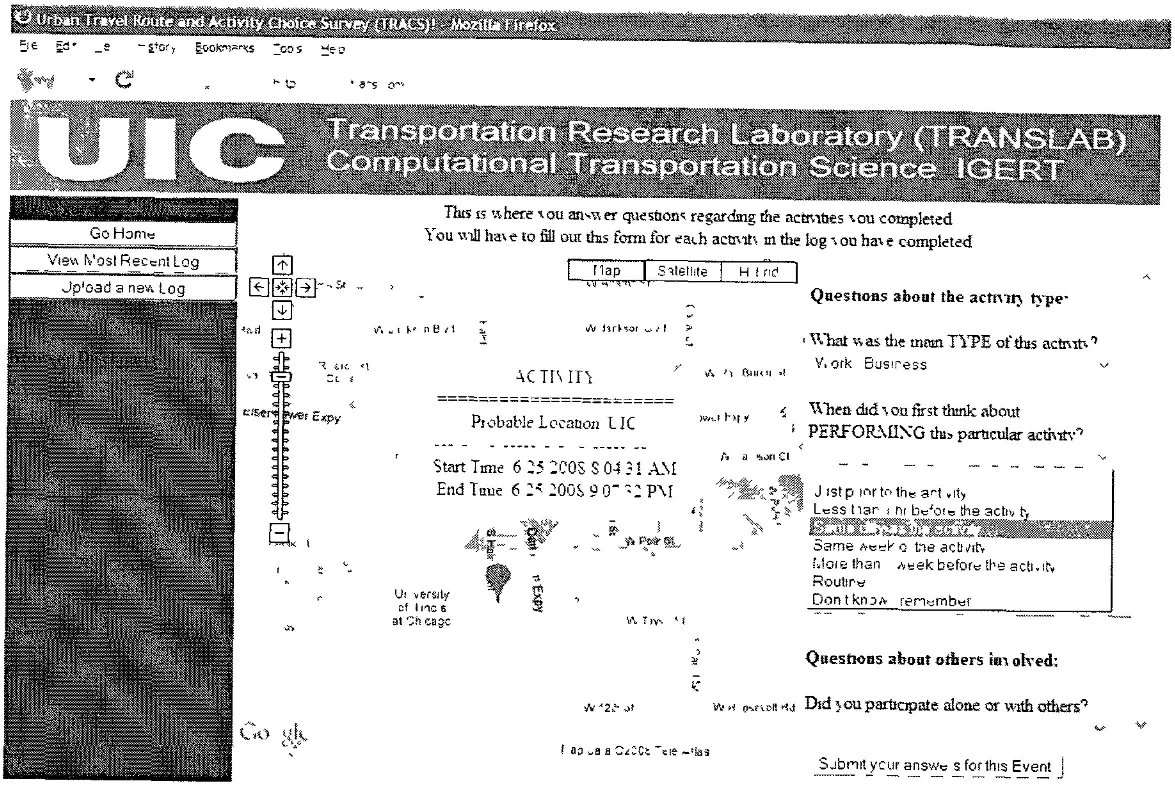


Figure 47. Activity Episode Questions Screen

For the "who with" questions, the respondent selects the number of involved persons, their relation to the respondent and the interpersonal flexibility associated with the activity, i.e. whether the participation of others was required or not. Location choice is another important component of the survey. The individuals are asked how many locations are generally available to them for performing this activity, the reason for choosing the selected location as well as the planning horizon for the location decision if it is different from the timing of the participation decision, (e.g. I need to go shopping tomorrow, vs. I need to go shopping tomorrow at Wal-Mart). Finally, some questions about the timing decisions surrounding the activity are asked. The planning horizon for the timing is selected in the same manner as for the location decision, again if it is different than the participation decision planning horizon (e.g. I will go shopping tomorrow vs I will go shopping tomorrow at noon). Additionally, general flexibilities of the start and end times are selected So for each attribute of the activity some basic descriptors are collected and then planning horizon and flexibility values are input which should further improve understanding of the underlying activity-travel pattern creation process.

The preceding discussion relates to survey questions asked about the attributes of the activities that the respondent engaged in. However, it is also desired to capture some of the decision processes that lead to mode and route choice decisions, which is possible through the use of GPS data collection in a way that has rarely been possible in traditional surveys. Because the exact route selected, travel time and distance traveled is known for each trip, it is relatively straightforward to display this information to the individual on a map and question them about the decisions that lead to the given outcome. In the current survey, for each trip identified in the validation stage, the mode and route choice questions shown in Figure 48 are asked of the respondents. The individuals choose the planning times and underlying reasons for both the mode and route choice decisions. These results, when coupled with activity type, flexibility measures, and other process data, can help to further understand mode and route choice behaviors in the full activity travel context of the individual

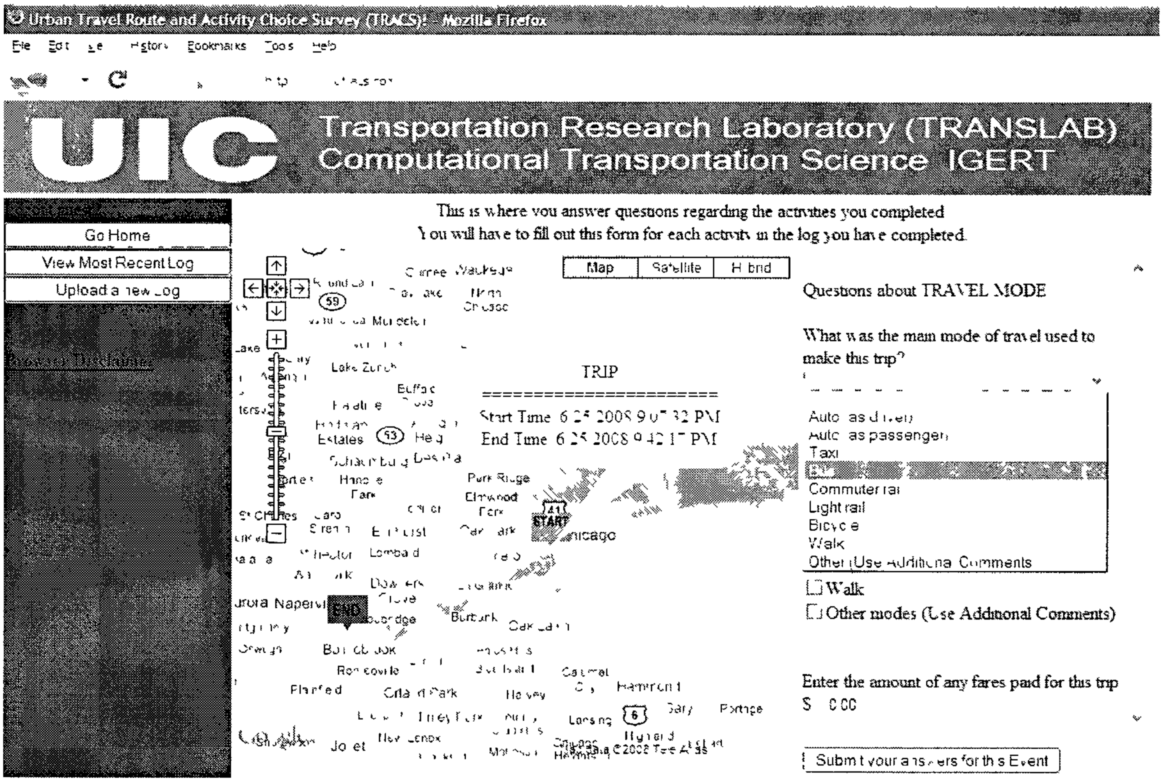


Figure 48. Travel Episode Question Screen

This section, combined with the previous data preparation section, has described the processes of creating a fully-automated prompted recall diary from data collected using GPS data loggers. However, running the survey as described without any further modification would still involve fairly significant respondent burden. In fact, during the pilot study, respondents identified many areas which were felt to be especially burdensome. It was felt that these shortcomings could inhibit the use of the survey for longer term data collection. The next section describes some techniques used to address these shortcomings.

19.4. Prospective Activity Attribute Planning Survey

In addition to the basic prompted recall survey, an additional preplanning survey was also implemented and used to capture respondents' prospective estimations of their activity preplanning processes. The Activity Preplanning Survey is shown in Figure 2 below. The preplanning survey is similar in conception, though much simpler in execution, to the CHASE survey (Doherty et al. 2004). The Activity Preplanning Survey asks the individuals at several points during the survey process to update their planned activity schedule for a fixed "Activity Preplanning Date" set eight days after the survey is begun. The individual can enter new activities and update existing activities during the Preplanning Survey. Any individual attribute for an activity can be defined as the activity is added, added at a later time or left blank. The individual is instructed when the Preplanning Survey is undertaken to only enter activities and attributes which they have already thought about into the preplanned schedule, although it is possible that the use of this survey format has the potential to prompt additional planning.

With the preplanning survey being conducted eight, two and one day before the survey date and all of the additions, modifications and deletions to the preplanned schedule being recorded, a record of all of the plan horizons for each activity and activity attribute for the preplanned day can be reconstructed and compared to the prompted recall results for the same day. Activities and attributes entered on the first preplan survey (eight days before preplanned day) roughly correspond to the "More than 1 week before the activity" plan horizon, while activities entered on the second survey (two days before preplan day) correspond to the "Same week as activity" plan horizon while anything entered on the last survey would be similar to the "One day before the activity" category. Anything that is executed in the actual survey but not recorded can be considered "Same Day/Impulsive". While "Routine" activities are queried from the users prior to the start of the survey in the upfront interview, it is likely that the user will not always be able to predetermine all of their routine, so routine activities are some combination of those activities entered in the upfront interview plus a portion of the activities entered on the first preplan survey. Thus, these two categories are combined into one for later comparison purposes.

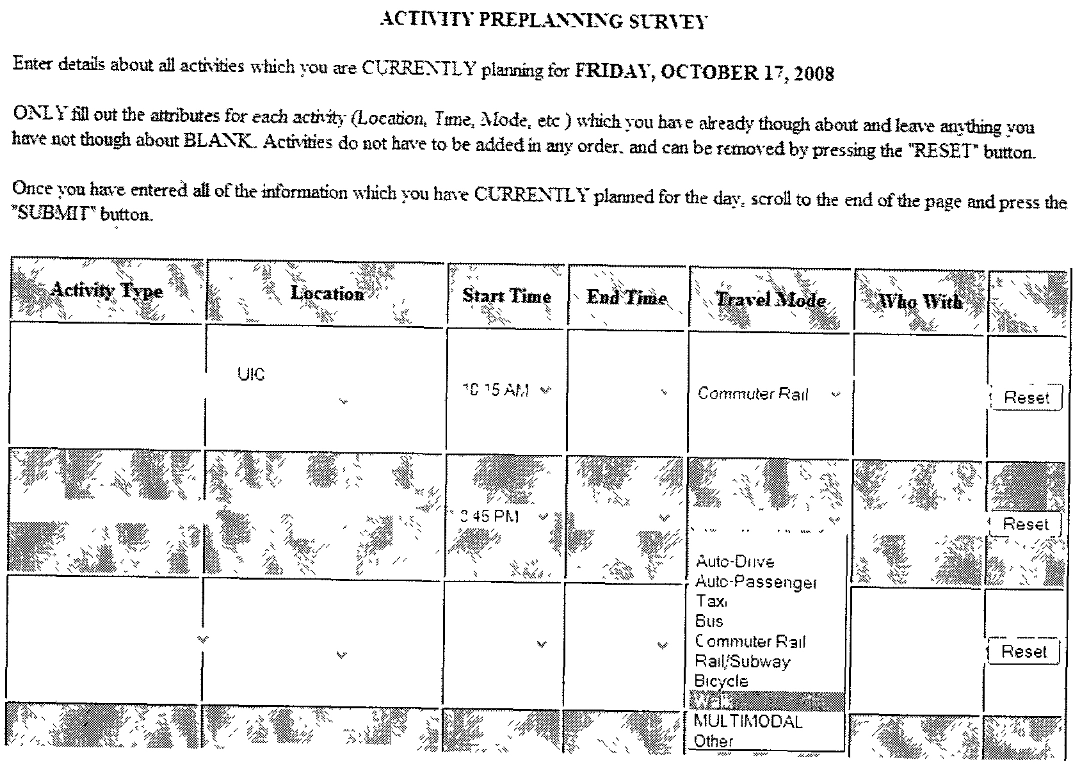


Figure 49. Activity Preplanning Survey Screen

This portion of the activity-travel survey was intended primarily to determine how well the survey respondents' prospective estimates of when different activities and their attributes were planned compared to the responses given during the prompted recall portion of the survey. While there has been much work on validating prompted recall data in terms of the recall of activity-travel pattern characteristics, usually in the form of comparing pen and paper diaries to prompted recall diaries derived from simultaneously collected GPS data (Wolf et al. 2004), there has been little previous work on evaluating the validity of prompted recall estimates of cognitive processes in travel behavior. As his was the primary purpose motivating the development of UTRACS having some data to validate against was important.

20. REDUCING RESPONDENT BURDEN THROUGH LEARNING

In order to further reduce the burden placed on survey respondents to enable longer duration surveys, the frequency and type of questions asked of participants needs to be significantly reduced. Some routines have been developed to accomplish this, as discussed previously, by automatically detecting some attribute which would negate the need for questioning the individual. Examples of these routines include automated trip purpose detection (Wolf 2000) and mode identification (Tsui and Shalaby 2006). However, these procedures are less applicable for most other attributes which are required from the current survey. It is not obvious, for example, how planning horizons, decision variables and other attributes such as involved persons could be derived from the GPS/GIS data alone. Therefore, a learning approach is needed, which utilizes information already collected in the survey to develop patterns which can predict the various activity-travel attributes. This section discusses some background in machine learning and some ways in which it has been applied in travel pattern prediction as well as propositions for using it to help reduce survey respondent burden.

20.1. Background

In data mining and machine learning related work, techniques for learning sequences, referred to as sequential associative mining, have been extensively studied since the original associative mining and later sequential mining techniques were introduced (Agrawal et al. 1993, Agrawal et al. 1995). Identifying patterns in traditional associative mining relies on multiple training sets for its primary constraint support. With associative sequence mining, there is a similar dependency on multiple training sequences. The implication of this when applied to the context of transportation is that for a travel or activity pattern to be significant, the pattern must be present across multiple travelers. While this constraint is likely a good guideline for predicting traveler patterns in general, if the goal is to predict the travel pattern of an individual, as is the case with travel surveys, then patterns that are unique to that individual are likely significant for predicting future behavior of that individual even if they have little predictive value for the set of all travelers as a whole. In addition, these techniques are not well suited to lengthy sequences as the distance between sets within a sequence is not accounted for. Applying this logic within the context of transportation would be equivalent to saying the likelihood of an event occurring is just as dependent on an activity that occurred four days ago as it is on the previous activity. While such relationships may exist, it seems reasonable to assert that activities that occurred in the traveler's recent history are in general more likely to be better predictors of the immediate next activity.

As noted above, the related applications of GPS-based prompted recall survey data falls into two general categories: micro-simulation, and individual travel prediction. In the area of micro-simulation, related work has primarily focused on using activity survey data for generating simulated activity schedules or verifying simulation results (Přibyl & Goulias 2005, Lee and McNally 2003). Recent work has examined using mental maps and cognitive learning for improving choice models through observations during micro-simulations (Arentze and Timmermans 2005). Other work has focused on predicting next location of individuals based on GPS traces (Ashbrook and Starner 2003). Liao et al. (2004) extended this idea and examined this problem as an unlabeled activity model for predicting the next location.

One of the few examples of using learned patterns to reduce respondent burden within an actual survey occurs within the ANNE survey developed by Marca et al. (2002). In the initial development of the survey, answers to previous activity-location questions were stored and later used for future activity locations to estimate likely activity types based on either the distance and time difference from currently labeled points, or later to develop an activity-type probability distribution over the survey area. This allowed likely responses to be suggested to the user and also was suggested for use in what the authors termed "focused questions", where users are only asked about activity locations which are not known with high probability. Currently there are no activity-travel surveys which utilize data mining techniques in the survey development that the author's are aware of.

20.2. Uses of Learning in GPS-Based Prompted Recall

In GPS-based prompted recall surveys, understanding the context of a traveler and being able to predict their likely next step can be used to help reduce participant burden in the form of data entry requirements. Depending on the goals and participant willingness, there are two different ways these predictive models could be applied: auto population or selective querying.

For auto population, the predictive model would be applied and questions about activity or travel could be pre-populated based on the user's prior history to be confirmed or changed by the participant. Consider a scenario where a five minute stop on the way to the train station was identified in the GPS data. If the participant's prior activity-travel pattern showed they occasionally stopped in this location for coffee, this information could be used to auto populate the activity type, the end time flexibility, and the likely planning horizon for the activity without the participant needing to enter it manually.

For longer term surveys, this type of predictive model could be incorporated to reduce the number of questions asked in a selective querying strategy. Two possible approaches would be high confidence elimination or key event querying. The principle behind high confidence elimination is to eliminate any question where the confidence that the answer is known is over a certain threshold. An alternative to this more suited for longer term surveys would be to only ask about activities or travel that are unusual compared to known patterns. In both of these approaches, while the participant still has a significant burden early on, as the survey progresses their burden is reduced as the application learns their behavior. While learning patterns specific to a participant are valuable, due to the amount of time necessary to observe these trends, augmenting the data with the patterns of others can likely help to reduce the initial learning time.

These learning models can therefore be used to either assist or completely replace the data entry requirements of the respondent. Depending on the length of the survey and the types of attributes required, this can help to significantly reduce the respondent burden, although as mentioned the burden during the initial phase of the survey could still be somewhat large as the algorithms learn the user's likely activity-travel patterns. However, this could further be reduced through the use of a well designed up-front survey of the person, which in addition to capturing socio-demographic information could also be used to identify common locations visited and routines within the respondent's usual activity-travel pattern. The use of initial inputs of this type would likely reduce the time needed for the algorithms to develop a useful predictive model.

21. CHICAGO-AREA DATA COLLECTION EFFORTS

21.1. Survey Implementation

The UTRACS survey system that was described in the preceding Chapters was implemented in the Chicago region from March 2009 through March 2010 (Frignani et al. 2010). Data was collected for a split sample of elderly and non-elderly residents in four counties (Cook, DuPage, Will and Lake) in the Chicago Area. Each respondent participated in the survey for approximately fourteen days. The survey collected daily data on activity-travel patterns, planning horizons, flexibilities, persons involved and travel costs. In addition, the survey registered the schedule evolution and the observed outcome for a single set day for each respondent during the survey period through the attached Preplanning Survey. This chapter focuses on implementation details for the Chicago UTRACS survey.

21.1.1 Methodology

The data collection portion of the UTRACS survey had three primary parts. The first part involved the collection of pre-survey information, including socio-demographic information, routine activities, and frequently visited locations. The routine activity and frequently visited location inputs allowed the survey software to automatically identify activity and travel attributes and to avoid repetitive questions during the main data collection process. This was implemented, in response to pilot feedback, with the goal of reducing respondent burden in the long run. For the routine activities, a weekly activity schedule was displayed in a tabular format where users could input the activity type, location, persons involved, start, end time and their variability, as well as days of the week when that activity was routinely performed. For the frequently visited locations, a Google map was displayed and respondents could enter the location address or a nearby intersection. The exact location point within a block or large building could then be specified dragging a pointer.

The second part consisted of the periodic activity planning survey previously described in Chapter 19.4. Data on the activity type, location, start and end time, travel mode, and persons involved was collected for a fixed day, which in this case was set to eight days after the user registration date. The planning survey page is shown in

Figure 49. This survey was repeated at intervals of three days and one day before the scheduled "preplanning day" occurred. During each iteration of the preplanning survey, the respondents entered only the attributes which were known at the time of the preplanning survey which allows the planning horizons to be imputed. For example, if an individual planned an activity of a certain type, but no attributes of the activity were known (other than the date), he would enter only the activity type on his preplanned schedule, leaving the attributes blank. Then, the next time the preplanning survey was invoked, the respondent could fill in values for some of the missing attributes, thereby fixing the plan horizons for those attributes as well. The outcome of the planning day was also recorded as part of the regular UTRACS surveying process and could then be used to validate the prospective survey.

In the final, major part of the survey, respondents carried a personal GPS logger for two weeks and uploaded their logs on the survey website at the end of each day as described in Chapter 19. Each respondent was given a unique login and password for the survey website. To facilitate data uploading, a Java program was installed on the data loggers as an "Autorun" executable which performed several cleanup and administrative tasks for the respondents automatically. Whenever the logger was plugged in through a USB cable to a computer, the Autorun program searched for logs collected on the logger since the last login, compiled the logs into a single file in a compressed data format and opened a web browser to the survey website with the users login information pre-populated. This removed all potential user errors in getting the data to the web-server by essentially making it a three-step process: 1. plug in the device 2. enter the password and 3. select log-file on the device. It was originally hoped to remove step three from this process to further simplify the procedure, but it was found that the log files could not automatically be uploaded to the server for security reasons.

The data in the log file were then transferred to a web server operated at the University of Illinois at Chicago and analyzed automatically to instantly produce a timeline and map as seen in Figure 46, displaying the activities and trips that were found. Users were prompted to correct errors in the log associated with signal acquisition delay, bad satellite fixes or occasional failures of the location finding algorithm. After user verification was done, the survey software generated a questionnaire for each activity and trip undertaken as seen in Figure 47 and Figure 48. For travel episodes, questions were asked regarding mode (including multiple modes), when and why decision for using said mode were made, costs, and why the respondent chose to take the displayed route. For activity episodes, questions regarding activity type, persons involved, activity, location, start time and duration planning horizons as well as interpersonal, location, mode, start time and duration flexibilities were displayed. These steps formed the major portion of the UTRACS implementation. The survey equipment used in the survey is described in the following section.

21.1.2 Survey Equipment

The survey equipment consisted of GPS trackers, rechargeable AAA batteries, chargers and computers with an internet connection when respondents' did not possess their own. The AMOD AGL3080 GPS tracker has a storage capacity of approximately 360 hours of tracking data and can operate for 15 continuous hours before the batteries need to be recharged. The GPS tracker is driverless and the Java code that processes the raw data recorded by the GPS tracker is stored in the device itself. The survey software is hosted on a web server operated out of the University of Illinois at Chicago. In this manner, no file has to be installed on the computer where the survey is taken. The data processing algorithms contained in the GPS device are coded in Java. This allows any computer with a working USB port, mouse, screen, internet connection and Java Runtime Environment to be used for the survey. Thus, respondents have the flexibility to complete the survey using different computers if they wish to do so. Laptops with dial-up or broadband internet access were provided to respondents with no access to a computer to preclude introducing biases against non-computer owners.

21.1.3 Respondent Recruitment

A total of 112 individuals in 101 households from the Chicago area were surveyed. Respondents were recruited from a random stratified sample of the Chicago area population. Half of the sample consisted of individuals age 65 and over and the other half of ages 18 to 64. The geographical area included Cook, DuPage, Lake and Will counties. This sample was stratified by county and by four categories of income. The sample followed the geographic population distribution existing in Census 2000. However, because of past experience of lower response rate among lower income and lower education households (Mohammadian et al 2009), those falling in the lower income categories were oversampled to yield a final income distribution similar to that of Census 2000. Individuals were provided with $25 gift cards for participating and entered a raffle for a $500 prize for every day completed.

21.2. Data Validation

Forty-eight percent of respondents were seniors aged 65 years-old or over, while the remaining 52% were between 18 and 64 years-old. Data on 2,612 trips and 2,891 activities were collected from the seniors and 3,015 trips and 3,285 activities from the remaining respondents, totaling 5,627 trips and 6,176 activities. The trip rate was 4.5 trips per person per day for both seniors and non-seniors, which indicates an above average number of trips when compared to the reference trip rate for personal travel suggested in Stopher et al.(2008) of 3.4 trips per person per day. This result is consistent with the finding of previous studies which demonstrate that GPS surveys have improved ability to capture trips which are frequently under-reported in other types of survey. The non-mobility rate was 9.35%, falling in the range suggested as accurate in Madre et al (2007).

21.2.1 Response Rate

The response rate was calculated using the American Association of Public Opinion Research (AAPOR) RR3A formula:

$$RR3A = \frac{SR}{(SR + PI) + (RB + O) + e_A(UH + UO + NC)} \tag{40}$$

Where,

RR3A = response rate
SR = complete interview/questionnaire
PI = partial interview/questionnaire
RB = refusal and break-off
NC = non-contact
O = other
UH = unknown if household occupied
UO = unknown other
eA = estimated proportion of cases of unknown eligibility that are eligible

The proportion of cases of unknown eligibility which would have been eligible was estimated using the overall rate of ineligible individuals to contacted individuals. Under 3% of households to which a phone contact was attempted were considered ineligible due to having health conditions that did not allow travel or survey completion, moving out of the study area or wrong contact information.

The overall response rate, in terms of persons, was 11.95%, and in terms of households, 11.31%. This response rate is low when compared to traditional one or two-day pen-and-paper travel surveys, but is satisfactory for a more complex two-week GPS-based internet survey that requires a greater commitment from respondents. Other long-duration surveys had comparable response rates (Doherty et al. 2004, Axhausen et al. 2007). The cooperation rate, which is the ratio of respondents to eligible persons contacted, was 17.36%. The response rate for the elderly was 9.65%, lower than that for the non-elderly, which was 14.67%. The lower survey acceptance among older individuals was likely due to the survey being internet-based. In fact, the most common reason elderly individuals gave for refusing to participate in this survey was the need to use a computer, even though a laptop with mobile broadband internet connection and technical assistance was provided. However, as years go by this problem should become less of an issue since the aging population will likely yield more seniors that are computer literate. Most of the younger individuals explained their refusal with lack of time availability, as did some of the elderly. This problem affects all types of surveys and survey modes. Enhancements to reduce the burden of the survey further can help in mitigating this type of refusal. A few individuals, both elderly and non-elderly, refused to participate in the survey because they felt that the full tracking of their activity-travel pattern was too invasive, even though they were informed that data is kept strictly confidential and unidentifiable. However, the overall refusals for this reason were low.

21.2.2 Sample Bias

Bias is a systematic error that can occur in the data collected from a sample of the population because individuals with certain characteristics may be more likely to be included in the sample than others. According to the recommendations in Stopher et al. (2008), the following variables were tested for sample bias: household size, vehicle availability, household income, age, race and gender. The categories tested for each of these variables were aggregated when compared to the recommendations cited due to reduced sample size of this survey. The total error is measured using the percentage root mean squared error (RMSE):

$$PercentRMSE = \sqrt{\frac{1}{n_i}\sum_{i=1}^{n_i}\frac{1}{n_{ij}}\sum_{j=1}^{n_{ij}}\left(\frac{r_{ij}-s_{ij}}{r_{ij}}\right)^2} \times 100 \tag{41}$$

where:

ni = number of variables i;
nij = number of categories j in variable i;
rij = reference value of variable i in category j;
sij = sample value of variable i in category j.

The reference values were calculated with data from the American Community Survey for Cook, DuPage, Lake and Will counties. TABLE XXVII presents the reference values and sample values for each variable mentioned. The geographic distribution of the respondents is also shown in TABLE XXVII and is compared to that of the Census 2000. Cook County, which encompasses the city of Chicago and the core of the metropolitan area, is in a small part over represented, but overall, the distribution of respondents satisfactorily matches that of the study area population. For the elderly subset, the RMSE is 49.15%. The sample characteristic that most contributed to the inflation of the RMSE for this subset was household income, because of the over representation in the sample of elderly households with income between \$75,000 and \$99,999 per year. For the non-elderly, the RMSE is more satisfactory: 38.53%. For this subset there was a lower participation of individuals younger than 45 years-old and an over-representation of female respondents.

There are currently no recommendations for an acceptable value of the RMSE measure for household travel surveys (Stopher et al. 2007b). However, due to the small sample size of the survey it is felt that the values calculated above are acceptable until larger scale surveys of this type can be fielded, provided that caution is used when utilizing the socio-demographic data in modeling procedures. It is for this reason that demographic variables are generally included in the models described in Part I of this thesis as simple indicator variables (i.e. senior v. non-senior, high v. low income) rather than continuous variables.

TABLE XXVII
SURVEY SAMPLE BIAS EVALUATION

Variable	Census: Elderly	Sample: Elderly	Census: Non-Elderly	Sample: Non-Elderly
Geographic Distribution				
Cook County	77.27%	81.25%	71.80%	84.00%
DuPage County	10.88%	10.42%	12.32%	8.00%
Lake County	6.73%	6.25%	8.92%	6.00%
Will County	5.12%	2.08%	6.96%	2.00%
Household Size (Average)	1.91	1.82	2.93	2.81
Vehicle Availability				
No vehicle	21.90%	4.44%	10.83%	4.65%
1 or more vehicles	78.10%	95.56%	89.17%	95.35%
Household Income				
$34,999 or less	50.33%	22.22%	24.38%	15.79%
$35,000 to 49,999	14.37%	19.44%	12.92%	21.05%
$50,000 to 74,999	14.97%	16.67%	19.63%	13.16%
$75,000 to 99,999	7.85%	22.22%	14.63%	15.79%
More than $100,000	12.49%	19.44%	28.44%	34.21%
Race				
White	73.55%	82.00%	61.12%	80.39%
Black/African American	17.37%	16.00%	19.12%	11.76%
Other	9.07%	2.00%	19.77%	7.84%
Gender				
Male	39.76%	34.00%	47.31%	30.77%
Female	60.24%	66.00%	52.69%	69.23%
Age				
18 to 44 years-old	-	-	61.33%	32.69%
45 to 64 years-old	-	-	38.66%	67.31%
65 to 74 years-old	51.74%	68.00%	-	-
75 years-old and over	48.26%	32.00%	-	-

21.2.3 Missing Value Index

The socio-demographic part of the survey contained 25 questions. The activity questionnaire had a minimum of 6 questions and a maximum of 13. The number of questions varied depending on the answers chosen. For example, if the person chose activity type "working at home", the questions about location and persons involved would be hidden because the location is already known from the previous answer (home) and the details of in-home activities are beyond the scope of this study. The trip questionnaire had a minimum of 6 questions and a maximum of 11. In the same manner as the activity questionnaire, the number of questions varied depending on the answers. If a respondent selected "bus" as the travel mode, for example, a question regarding fares would appear, while if the mode was "walk", no further question would be asked.

Out of a total of 61,004 applicable questions, the survey had 2,687 refusals and 308 "do not know" answers. Calculating the missing value index according to the recommendations in Stopher et al. (2008), the index for this survey is 0.0483. The questions that had the highest item non-response rates where those regarding the decision-making process: when the decisions for activity duration and start time were made and how flexible were these attributes. This result indicates that questions regarding decision-making process are more difficult to answer than those which refer to more explicit aspects of travel and activity pattern such as travel modes, activity type and accompanying persons. This difficulty might be due to the fact that individuals often do not think about their decision-making process, so answering questions such as "when did you decide on the activity duration?" or "how flexible was the activity start time?" requires more mental effort than indicating which travel mode was used in a trip. As survey participants became accustomed to thinking about their decision-making process, answering these questions became easier.

21.2.4 Assessment of Respondent Burden, Fatigue and Conditioning

The average time respondents spent to confirm and correct the estimated activity-travel pattern was 12 minutes and 46 seconds per day. The average time spent to answer a questionnaire page for one activity was 1 minute and 54 seconds and for one trip, 1 minute and 18 seconds. Because respondents could perform other activities while filling in the survey, only the values belonging to the 85th percentile were used to calculate these averages. Additionally, it is estimated that respondents spent several minutes on the additional daily steps of the survey: connecting the device to the computer, uploading the log and changing device batteries.

At the end of the survey, respondents were asked to fill out a short evaluation about their overall experience with the survey. The form contained seven Likert-type questions relating to the difficulty of the survey and two yes or no questions. The scale for the Likert-items had five values, ranging from strongly disagree to strongly agree. It also had a space for comments about the survey. In this evaluation, about 35% of the respondents classified the survey as difficult to complete. For the elderly subset, however, 53% of respondents disagreed that the survey was difficult, and for the non-elderly, 63% shared the same opinion. About 64% of respondents considered that the daily time required to complete the survey was too long, while 23% considered it was not too long. Among the non-elderly, the feeling that the survey required a long time was stronger than among the elderly. This is consistent with the fact that many of the elderly participants are retired and therefore do not have as much time pressure as full-time workers and students.

On the other hand, 60% of the respondents did not believe that the participation period of 14 days was too long while only 14% of respondents thought that it was. This result indicates that GPS-based prompted recall surveys over the internet have a tremendous potential for long term applications. Since the daily time necessary to complete the survey is one of the largest drawbacks for the respondents, the burden can be significantly reduced by shortening the daily time commitment. Consequently, the survey period may potentially be extended for over two weeks. Data mining techniques such as sequential associative mining can help to decrease the questionnaires' length without losing important data through both auto-populating likely answers and selectively removing questions that can be inferred with a high degree of confidence as discussed in Chapter 20. While many attributes can be populated with reasonable confidence based on patterns commonly observed across all travelers, one of the advantages of a long term survey is the opportunity to tailor the predictions to the individual. A more specialized model is likely to result in higher confidence in predictions and better coverage of the number of fields that can be auto-populated. In a long term survey with sufficient time to build a reliable model of the individual, machine learning can provide significant reduction in respondent burden (Williams et al 2009).

Additional key concerns in extended duration surveys are fatigue and conditioning. Survey fatigue refers to the situation when respondents get saturated with survey burden and stop completing the survey tasks with the necessary commitment. Examples of survey fatigue are activity and trip rate decline, inconsistent answers and increase in item non-response over the course of the survey. The second issue, survey conditioning, is related to the influence that the survey itself may have on respondents' behavior. For example, by reflecting about his activity-travel pattern while answering the survey questions, a respondent may find opportunities to optimize his schedule. Or, the realization of the amount of unplanned activities performed daily may induce a respondent to change his scheduling behavior. Similarly, seeing trips on a map might induce respondents to reroute to shorter paths.

The assessment of both of these issues is usually made by examining the trip/activity rates over the survey duration (Axhausen et al. 2007). Figure 50(a) shows the average number of activities over the duration of the survey. In this same figure, one can see the average time spent to answer one activity questionnaire page. Figure Figure 50(b) shows the same information for trip episodes. In both cases, the average time spent answering each questionnaire page decreased by approximately 2.2 seconds per day, while the average number of activities reported per person decreased at only 0.03 per day (a result skewed somewhat by an inordinately high average number of activities completed on the third day across all users). There was essentially no decline over the life of the survey for each respondent in the number of episodes entered. Figure 50(c) shows that the missing value index for each day declined an average of 5% over the course of the survey, which reveals that the reduction in time spent answering the survey was not due to skipping questions, as would be expected if survey fatigue was present. Figure 50(d) and Figure 50(e) demonstrate the evolution of activity type and activity plan horizon over the duration of the survey, which had an average change of less than 0.6% per day, indicating that answers remained consistent throughout the 14 days. Finally, Figure 50(f) shows the evolution of travel time and distance, which also remained fairly stable over the duration of the survey. These results indicate that there were no significant changes in activity travel patterns over the course of the survey for respondents, i.e. respondents were not learning from previous responses how to reduce travel time, plan more efficiently, engage in more optimal activity patterns, etc. So survey conditioning also does not appear to be much of an issue in this study.

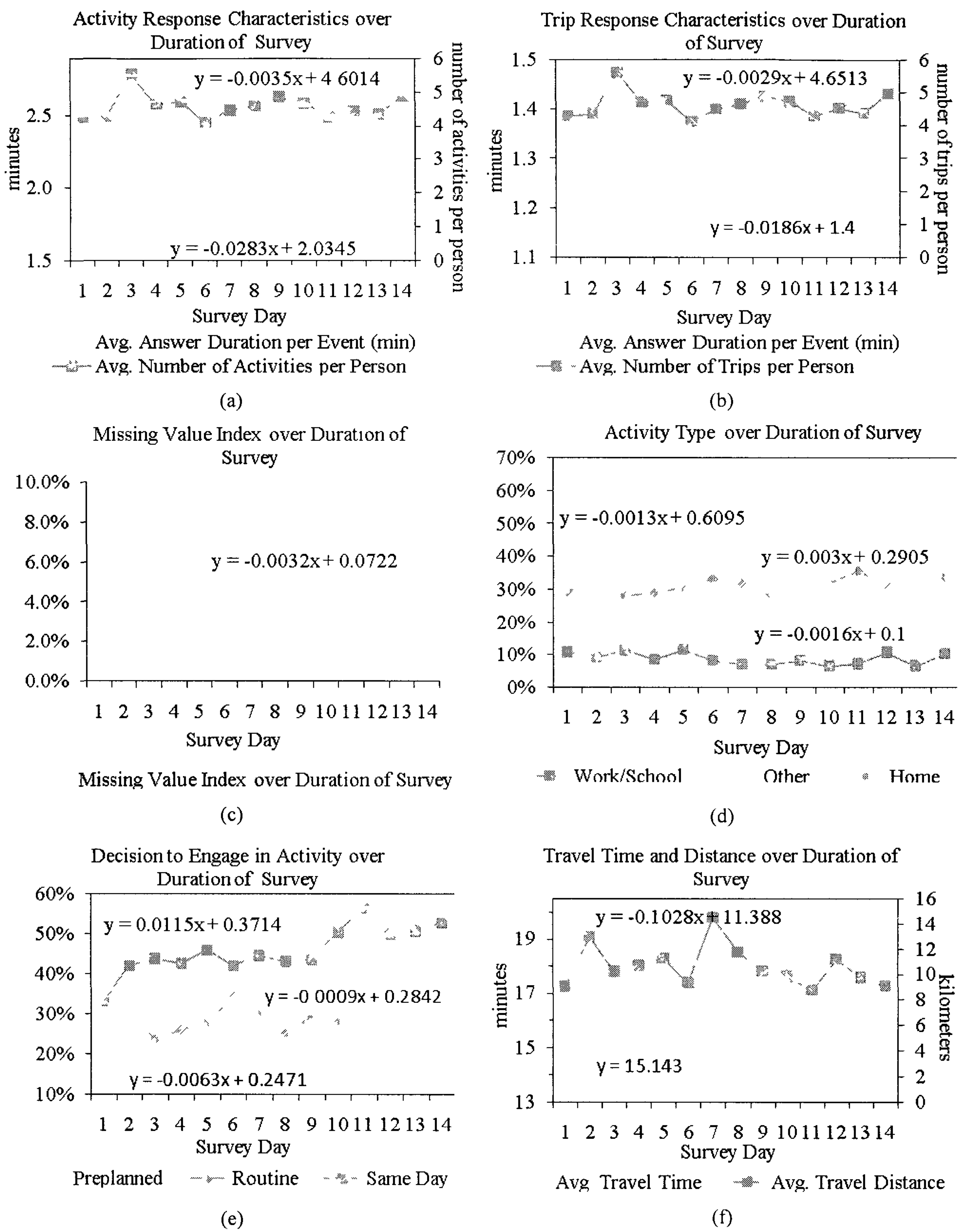


Figure 50. Survey Fatigue and Conditioning

(a) Activity responses characteristics, (b) Trip responses characteristics, (c) Missing value index, (d) Activity type, (e) Decision to engage in activity, (f) Travel time and distance.

21.3. Conclusions

This chapter has documented a successful implementation of the UTRACS survey for the Chicago region. This survey is significant as it is the first to focus specifically on the activity planning dynamics of individuals in a comprehensive manner, building on the previous work in this field started by CHASE (Doherty et al. 2004). Although the sample size of the initial survey is quite small, as is often the case with detailed GPS surveys of this type, the length of the survey ensures that there is a considerable number of activity-travel observations to use in model estimation. This is especially important when considering topics such as planning dynamics and other time-dependent features of the activity scheduling process. Essentially surveys of this type trade of breadth across the population for depth within a limited population in terms of activity travel responses.

The Chicago UTRACS sample contained information on over 6,000 individual activity observations and nearly as many travel episodes. The data was shown to be relatively free from bias considering the size of the sample. The high trips per person average of 4.5 and low non-mobility rate of 9.7% indicate quality data in terms of recent standards proposed for personal travel surveys (Stopher et al. 2008). The next section documents a preliminary data analysis of the UTRACS survey results in terms of activity-travel pattern characteristics and the activity planning process observations, as these are the primary purposes behind conducting the UTRACS survey.

22. CHICAGO UTRACS SURVEY RESULTS

22.1. Introduction

The dynamics of the activity scheduling process have only begun to receive attention in terms of data collection and modeling effort. The CHASE© survey (Doherty et al. 2004) was the first attempt to collect data regarding the "Plan Horizon", a concept discussed at length by Doherty (2005). The plan horizon can be thought of as the "duration of time between the planning and execution of an activity" (Doherty 2005). This survey collected planning time horizons for activities planned and scheduled throughout a one-week period. Another recent attempt to capture the process of activity planning was the REACT! survey (Lee and McNally, 2001) which was derived from CHASE. Each survey tracks the formation of a weekly activity schedule through observing additions, modifications and deletions to a planned schedule and comparing them to a final executed schedule. REACT! added to CHASE the ability to leave aspects of an activity blank until they were known, in a similar manner to the design of the UTRACS preplan survey discussed in Section 19.4, and the ability to trace the underlying decision process behind the attribute changes (Lee and McNally, 2001).

The UTRACS survey attempts to collect the same information derived from the CHASE and REACT! surveys, namely activity and activity attribute plan horizons, but in a different manner. The UTRACS survey is designed as a prompted recall survey, meaning the planning horizons derived from it are necessarily retrospective in nature, as opposed to the prospective plan horizons derived from a CHASE-type survey. This difference motivated the inclusion of the preplanning portion of the UTRACS survey to emulate CHASE-type preplanning data collection. The results of a comparison of the UTRACS prompted recall results to this small prospective survey as well as directly to the CHASE survey data are used to validate the retrospective data collection of planning horizons. It would be beneficial if it could be shown that individuals show no significant difference between prospective and retrospective assessments of planning horizon, as prompted recall data is somewhat easier to collect than weekly scheduling data. However, it should be noted that prompted recall data does not produce the detailed observations on the activity planning and scheduling process such as conflict resolution and planned activity rates. Therefore prompted recall data is seen more as a supplement to the traditional household activity-survey rather than as a replacement for the weekly scheduling data collected by surveys such as CHASE.

Another reason for a validation data set, is that has been argued that respondents' descriptions of higher order decision or cognitive processes, such as the activity planning behaviors addressed here, are inherently unreliable (Nisbett and Wilson, 1977) and do not result in quality data. Others, however, have later determined that verbal reports regarding cognitive processes can be reliable as long as they do not require introspection about the process itself (Ericsson and Crusher, 1991; Ericsson and Simon, 1993). For this reason it was decided to collect retrospective reports about the results of the activity planning process (i.e. "when was this decision made", "what was decided", "how flexible was this choice", etc.) rather than attempt to have the individuals describe the process itself, as this was expected to produce more reliable data (Ericson and Crusher, 1991). The collection of both the prospective and retrospective data would then allow the level of reliability of the self-reported activity planning to be analyzed.

The remainder of this chapter details an initial descriptive analysis of the activity travel pattern results, followed by an analysis of the planning behavior observations found in UTRACS. A comparison between the UTRACS prompted recall plan horizon results to the preplanning survey results is also described. Finally, a comparison of the activity plan horizons derived from UTRACS is compared directly to the CHASE survey results.

22.2. Activity-Travel Pattern Attributes

A summary of the trip and activity attributes collected is available in TABLE XXVIII. The attributes are compared against those observed in the Chicago Metropolitan Agency for Planning (CMAP) 2008 Travel Tracker Survey (24). The Travel Tracker is a multimode household travel and activity survey which was collected from 10,552 households in a 1 or 2-day survey on the Chicago metropolitan area. Telephone interviews were the primary data collection mode. Over 23,000 individuals participated in Travel Tracker, out of which 4,315 were ages 65 and over. TABLE XXVIII displays the average number of activities by type per person per day and the percentages of accompanying persons, travel mode, trip duration, daily travel time, trip distance and automobile speeds for the elderly and non-elderly subsets.

TABLE XXVIII reveals that respondents reported a higher activity rate per person-day for almost all types of activities. Noticeably, at least 50% more shopping activities were reported in this survey than in the reference. The automated recording and detection of activities made possible that minor shopping activities such as stopping on the way and buying a drink be reported at a higher frequency. The same effect occurred to changes in transportation. Because these are usually short activities and people tend to think they are unimportant, the automated survey yielded a much higher rate of this type of activity than that observed in the reference, both for the elderly and non-elderly samples. Social, leisure, recreation and, specifically for the elderly, civic and religious activities were also observed at a higher rate here. Meanwhile long duration mandatory activities, such as working, were not over reported in UTRACS compared to the CMAP survey, and were in fact slightly lower due to the higher coverage of weekend activities in UTRACS. For accompanying persons and travel mode, this survey had comparable shares to the CMAP survey. On the other hand, consistent with findings of previous studies, this survey registered more short duration and short distance trips. The total daily travel time is overall lower, especially for younger travelers, and average automobile and bus speeds are higher. This result corroborates the observation that self-reported surveys overstate travel time and provides another indication of the improved activity and travel reporting achieved with the use of GPS technology.

TABLE XXVIII
SUMMARY OF ACTIVITY-TRAVEL ATTRIBUTES

Attribute	Value	CMAP: Elderly	UTRACS: Elderly	CMAP: Non-Elderly	UTRACS: Non-Elderly
Daily Activity Rate	Change transp.	0.02	0.11	0.06	0.07
	Healthcare	0.12	0.16	0.07	0.14
	Social/leisure	0.34	0.65	0.35	0.45
	Meal	0.22	0.33	0.26	0.23
	Other	0.41	0.60	0.54	0.47
	Personal Business	0.15	0.24	0.13	0.15
	Work	0.19	0.05	0.77	0.66
	Religious/Civic	0.10	0.22	0.06	0.06
	School	0.00	0.02	0.03	0.04
	Shopping	0.55	1.08	0.48	0.73
Party	Alone	68%	56%	70%	65%
	With Others	32%	44%	30%	35%
Daily Travel Time (min)	0 - 30	37%	38%	20%	33%
	30 - 60	20%	24%	19%	28%
	60 - 120	25%	26%	34%	28%
	> 120	18%	12%	28%	11%
Travel Mode	Auto drive	71%	72%	72%	78%
	Auto passenger	17%	14%	10%	12%
	Bicycle	0%	0%	1%	0%
	Bus	2%	5%	2%	1%
	Commuter rail	0%	1%	2%	1%
	Light rail	0%	1%	2%	1%
	Walk	7%	6%	9%	5%
	Other	1%	0%	2%	1%
Trip Duration (min)	< 15	64%	77%	60%	75%
	15 - 30	22%	16%	22%	19%
	30 - 45	6%	4%	8%	4%
	45 - 60	3%	1%	5%	1%
	> 60	4%	1%	5%	0%
Trip Distance (km)	< 5	55%	51%	50%	55%
	5 – 10	21%	22%	18%	15%
	10 - 20	14%	15%	15%	13%
	20 - 30	5%	5%	7%	7%
	30 - 50	3%	4%	6%	6%
	> 50	2%	2%	3%	2%
Avg. Speed – Auto (km/h)	0 - 30	62%	14%	54%	15%
	30 - 60	31%	69%	37%	66%
	60 - 90	6%	15%	7%	16%
	> 90	2%	2%	2%	3%

22.3. Descriptive Analysis of Activity Planning Process Data

The plan horizon and flexibility data obtained from the UTRACS survey Chicago implementation are shown in TABLE XXIX below. The table shows the total plan horizon observances for the overall activities, and the five primary attributes as well as the percentage of each plan horizon value within each activity/attribute. Note that there are fewer observations for the "Who With" and "Mode" attributes, as the "Who With" plan horizon was not asked for activities conducted alone and the "Mode" plan horizon was only asked when a preceding trip was present. In general, the aggregate results show that overall about 44% of activities are planned on the day of execution, with the rest divided between preplanned (previous day to weeks before) at 20% and routine activities at 29%. The party composition plan horizon distribution follows almost a similar distribution, while location and mode are generally more routine and the start time and duration are more impulsive than the overall activity plan horizon. It was also observed that individuals had a harder time determining the mode plan horizon with 23% of responses left blank or marked "don't know".

TABLE XXIX
ACTIVITY PLANNING HORIZON AND FLEXIBILITY RESPONSES

	Activity	Mode*	Who With**	Location	Start Time	Duration
Plan Horizons						
< 1 hr before	22%	14%	21%	17%	30%	47%
Same Day	22%	14%	20%	13%	21%	9%
Same Week	13%	12%	13%	10%	8%	4%
Preplan	7%	6%	9%	6%	5%	3%
Routine	29%	31%	28%	46%	28%	28%
Missing/DK	7%	23%	7%	7%	9%	10%
Flexibilities						
Inflexible		58%	64%	74%	25%	47%
Mod. flexible		42%	19%	12%	34%	32%
Highly flexible		0%	18%	14%	41%	21%
Total	6176	5236	3309	6176	6176	6176

* Only asked when a trip to an activity occurred.
** Only asked for activities conducted with other individuals.

The flexibilities shown in the table follow a similar pattern as the plan horizons. In general it seems that the attributes with the most impulsive planning tend to be those with the most flexibility, i.e. the start times and durations of the activities. Meanwhile, the most preplanned / routine attribute, location choice, has the least amount of flexibility in terms of planning with over 74% of location choices considered to be inflexible. This corresponds to the hypothesis that more planning effort represented by more inflexibility leads to longer plan times. This is intuitive as more flexibility leads to more choices which would then be easier to schedule, while fixed attributes require scheduling to work around them. This appears to be backed up by the observations in this study.

A potentially more informative way to view the planning time information is to see how the attribute plan horizons vary by the overall activity plan horizon, in order to evaluate any differences between when the respondents feel that an activity was planned and when the different attributes of the activity were actually decided on. These comparisons are shown in Figure 51, where the percentages of each plan horizon for each attribute are shown for four different aggregated activity plan horizons – Impulsive (combination of "Impulsive" and "< 1 hr"), Same Day, Preplanned (combination of "Same Week" and "Preplan") and Routine.

The figure shows that the individual activity attribute planning horizons are distributed about as expected. For "same day" planned activities, most of the activity attributes are also planned on the same day, with a significant percentage of the attributes also being considered routine, especially for location and mode decisions. This makes sense, as there should most likely not be many "preplanned" attribute choices made before the activity was decided on. An exception to this is for the mode choice, where due to trip-chaining the person may have already known they would be in an auto-tour, for example, and impulsively decided to stop for an activity. In this case the auto-mode could have been preplanned. The high level of routinely planned location and mode choices shows that even a lot of supposedly "impulsive" activities are still occurring at least in some aspects in a routine pattern.

For the "same day" and "preplanned" activities, the results show that indeed, most of the attributes are also "preplanned" (either same week or longer), with a smaller percentage of routine activities. These activities therefore are more likely to be planned as stand-alone trips requiring separate attribute planning rather than impulsive stops at routine locations along routine trips. The party composition, location, and travel mode are all almost entirely preplanned with some routine planning also. The timing decisions, however, remain somewhat impulsive, with over 10-20% of the start time decisions and almost 50% of the duration decisions occurring impulsively, showing the flexibility that remains in planning these decisions. In fact the duration of a preplanned activity tends to be quite flexible, with many decisions made during the execution of the activity.

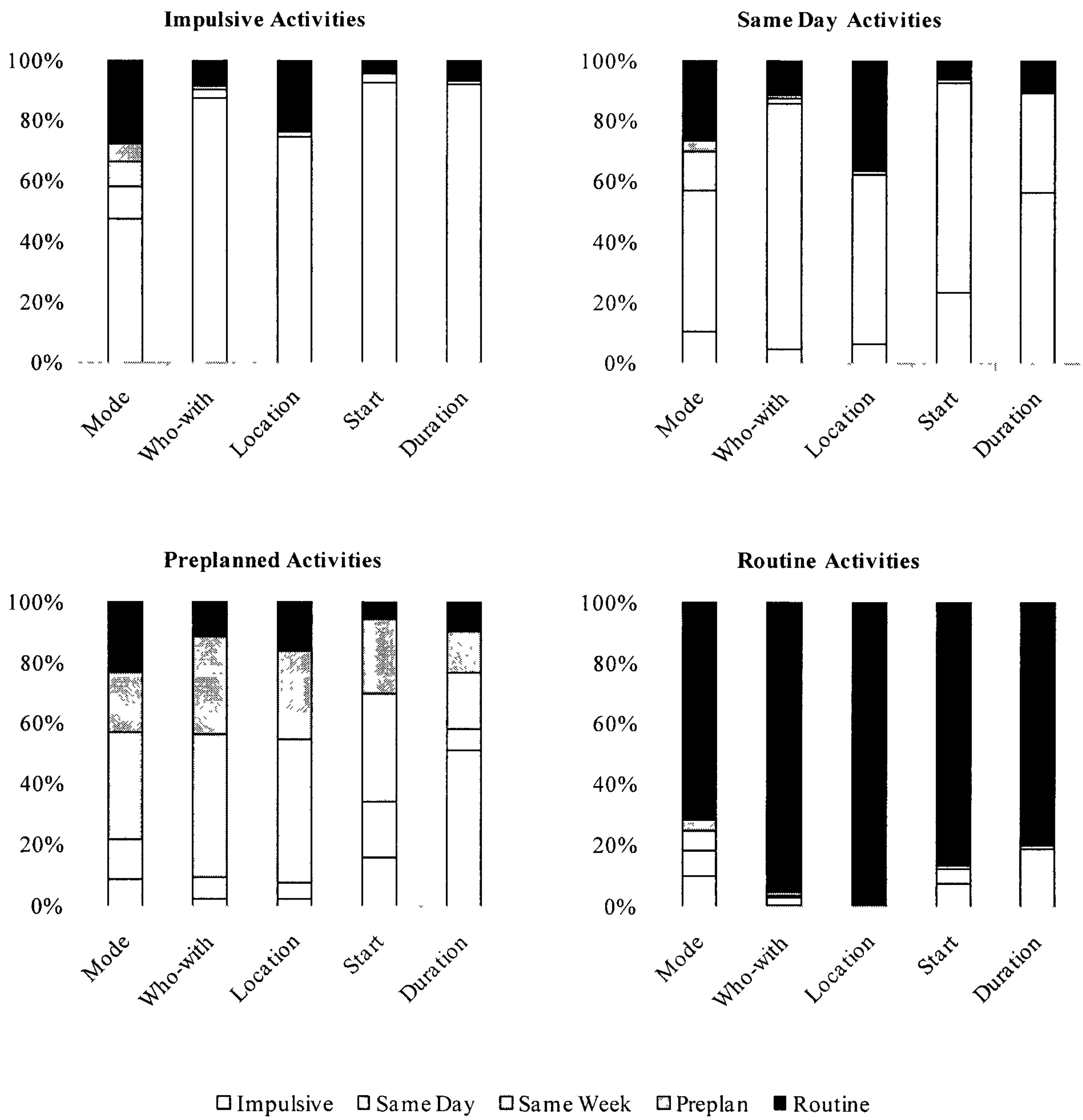


Figure 51. Activity Attribute Plan Horizon by Overall Activity Plan Horizon

Finally, the analysis of the "routine" shows that almost all attributes of a routine activity are also reported as routinely planned, with some flexibility in the timing, duration and mode choice for these activities Most activities classified as routine tend to be of the "mandatory" activity type, such as work, school, etc which usually occur alone and at a fixed time and place These tend to be long established parts of the activity travel pattern where the attribute decisions have already been made, although again, some of the timing decisions are still made impulsively, especially for the duration choice

Another way to analyze the planning horizon data is to compare the plan horizons for activity attributes with each other for the same activity, in other words, to look at the order in which the attributes are planned Since the number of potential activity planning orders is fairly large for five attributes (3,125 possibilities including simultaneous planning), the current analysis is limited to evaluating the first activity in the planning sequence The initial analysis is shown in TABLE XXX below

TABLE XXX
ANALYSIS OF FIRST PLANNED ACTIVITY ATTRIBUTE

1st Planned Attribute Routine?	Number of attributes planned 1st	Count*	% of Activities With Attribute Planned First				
			Mode	Who*	Location	Time	Duration
Yes	1	1227	33%	6%	52%	2%	7%
	2	530	46%	22%	75%	31%	26%
	3	736	28%	23%	96%	77%	77%
	4	750	70%	44%	99%	95%	91%
	5	245	100%	100%	100%	100%	100%
	Total	**3488**	**47%**	**27%**	**78%**	**49%**	**49%**
No	1	508	55%	14%	23%	6%	2%
	2	341	34%	38%	80%	38%	9%
	3	604	40%	49%	96%	85%	30%
	4	636	64%	86%	100%	99%	52%
	5	183	100%	100%	100%	100%	100%
	Total	**2272**	**54%**	**54%**	**79%**	**65%**	**32%**

* Excludes activities where the overall activity plan horizon was missing or unknown

The table shows all of the activities split into routine versus none routine first planned activities, then categorizes the activities by the number of attributes which were planned first, ranging from 1 to 5 (where all of the attributes were planned simultaneously). Then, each row of the table shows the percentage of time that each of the five activity attributes was planned first for the given routine and number of first planned activities. For example, the first row of the table shows that of all the activities, 1,227 were planned with only one attribute decided first where that attribute was routine. In 6% of these cases, the first attribute planned was the party composition, in 52% of the cases the location was selected first, etc. The total row for each section (routine and non-routine first attribute) shows the overall percentage of cases where the attribute was planned first, for example in 79% of non-routine planning cases the Location was selected first (possibly in combination with other attributes).

One encouraging result of this analysis is that there appears to be a fairly small amount of activities where all of the activity attributes were selected at the same time; in fact, less than 5% of total activities were planned in this manner. This shows that at least the survey respondents potentially thought about the planning of each attribute separate from the rest, rather than assigning the same plan horizon to all attributes in most cases (it is recognized, however, that planning all attributes at the same time is not necessarily erroneous).

The results show that the location attribute is most frequently planned first, especially when the location is a routine location, followed by the mode, timing and duration and finally the party composition. An interesting result shown in TABLE XXX is that activities where the attributes are non-routine exhibit a higher degree of simultaneity in planning, with more activities having two, three and four attributes planned at the same time, when compared to activities with a routine first attribute.

Finally, an exploratory analysis of the activity planning horizons is shown in Figure x. This analysis shows how the activity plan horizons vary along with various household and person level variables, such as the household size, income, number of vehicles, age, gender, education, etc. Also shown is the distributions of the plan horizons by the various activity attribute flexibilities. In general the distributions are all significantly different for each variable included at the 5% level under the chi-square test. However, the impacts of some of the variables stand out. High income households seem to have many more routine and far fewer impulsive activities than other households. Additionally, and perhaps for related reasons, households with more vehicles have many more routine activities than do households with no vehicles. Internet users and college graduates also show more routine activities than others.

TABLE XXXI
EXPLORATORY ANALYSIS OF ACTIVITY PLAN HORIZON

	Imp	Same	Same Week	Preplan	Routine	Total
HH Size=1	25%	22%	14%	9%	30%	1300
HH Size=2	19%	23%	17%	8%	32%	2743
HH Size=3+	26%	24%	10%	7%	33%	2255
HH Inc < 50k	27%	26%	14%	6%	27%	2054
HH Inc = 50-100k	22%	22%	15%	9%	32%	2213
HH Inc > 100k	18%	21%	12%	6%	42%	1129
Num Veh = 0	22%	30%	24%	7%	17%	304
Num Veh = 1	24%	23%	14%	9%	29%	1883
Num Veh = 2+	22%	23%	13%	7%	34%	4111
Non-senior	25%	22%	11%	6%	36%	3305
Senior	20%	25%	18%	9%	27%	2993
Female	20%	23%	15%	8%	34%	3900
Male	27%	25%	12%	8%	28%	2398
White	24%	23%	13%	7%	32%	5015
Non-white	17%	23%	20%	9%	31%	1283
Internet User	23%	24%	13%	8%	33%	5253
Not Internet User	21%	22%	20%	8%	29%	1045
College Degree	24%	20%	13%	7%	35%	3812
High School	22%	30%	16%	8%	23%	1935
No Telework	21%	24%	15%	8%	32%	4942
Some Telework	30%	21%	10%	6%	33%	1356
Start Flexible	23%	24%	16%	5%	32%	3191
Start Inflexible	22%	23%	12%	11%	32%	2550
Duration Flexible	22%	23%	15%	7%	33%	3323
Duration Inflexible	24%	24%	13%	8%	31%	2403
Who With Flexible	26%	22%	25%	11%	16%	1163
Alone	23%	24%	10%	4%	40%	3621
With Others	18%	23%	17%	18%	23%	1097
Location Flexible	40%	30%	20%	4%	6%	738
Location Inflexible	20%	23%	13%	8%	37%	4953

Non-seniors show both more routine and more impulsive activities than do seniors, perhaps relating to more mandatory, work-type activities with their attendant opportunities to make impulsive shopping or other stops. A final interesting note concerning the socio-demographics is that males have less routine and more impulsive activity planning behavior than do females.

The other interesting results of the analysis concern the relationship between attribute flexibility and activity planning. In general there is a significant but not strong correlation between the timing flexibilities and the plan horizon. However, there are highly significant and very large differences in activity planning when considering flexible versus inflexible activities in terms of interpersonal or location flexibility. Flexible location activities are almost exclusively not preplanned in advance, while fixed location activities are generally more routine, indicating the significant scheduling effort needed to plan for these activities. Finally, most activities done alone tend to be routine, likely work or other such mandatory activities. Meanwhile activities which required the participation of other require more preplanning effort and tend to be more routine than activities where the participation of others is optional, likely due to the greater schedule coordination needed to include more individuals in the same activity.

All of these analyses show how the activity planning characteristics can vary with different socio-demographic characteristics of individuals and even with other planning characteristics. In other words, some relationships between activity plan horizon and activity attribute plan horizon, and activity plan horizon and attribute flexibility, have been shown. These initial exploratory analyses formed the basis for the more advanced modeling seen in the development of ADAPTS, specifically in the models discussed in Chapter 9

22.4. Validation of Retrospective Activity Planning Behavior Reports

As stated previously, in order to validate the retrospective reports on activity and activity attribute planning times, a separate stand-alone activity preplanning survey module was included in the UTRACS survey, and was periodically updated by the survey respondents throughout the survey to reflect their current plans for the preplan survey day. This gives a basis for making an initial comparison between individuals' perception of the planning of activities as it is occurring with their retrospective accounts of when those decisions are made after the activity is actually completed, although it should be noted that due to the small size of the preplanning survey no firm statistical conclusions are available.

The initial results of the activity preplanning survey show that 78% of survey respondents completed the preplan survey, while approximately 42% of survey respondents have successfully completed both the preplan survey and completed the prompted recall survey for the preplanned day enabling the comparison analysis. This left preplanning results from 44 users where valid comparison to the retrospective data could be made. These 44 respondents preplanned a total of 84 activities on the preplan day, of which 62 were later executed according to the prompted recall results.

Alternatively, analyzing the prompted recall results obtained on the preplan survey days shows that 24 out-of-home activities which the respondents recalled as preplanned were not actually present in the preplanning survey out of a total of 92 such recalled activities. This could be due to either the individuals forgetting the activities when completing the preplanning survey (retrospectively correct) or due to the individual improperly remembering the plan horizon incorrectly (prospectively correct). However, less than 26% of activities classified as preplanned in the prompted recall survey were missing in the prospective data showing individuals have an acceptable ability to recall preplanned activities correctly. It is felt that prospective errors are most likely as the preplan survey is observed far less frequently than the overall prompted recall survey so the users have less experience with it and the format is more open ended so its possible that respondents can miss activities which really are preplanned but not recalled at the time of the preplan survey – i.e. nothing is prompting the recall of planning during this portion of the survey. However, it is still feasible that the errors in preplanning estimation occur on the retrospective side so more analysis is still needed to determine why differences are observed, perhaps through something like a think-aloud follow-up where interviewers can show the individuals the results of each survey and ask about the differences, similar to the work done by Clark and Doherty (2008).

In any case, comparison data was obtainable for the 62 activities which occurred in both the preplan and prompted recall survey. This comparison was performed to see how closely the prospective estimates of activity plan times corresponded to the retrospective reports. The results of the comparison can be seen in TABLE XXXII below. Note again that some aggregation of the potential plan horizon response categories has been performed due to the methodology of the preplanning survey, which was conducted eight, two and one days before the prompted recall survey of the preplanned day. Activities added one and two days before the survey day are considered "Same Week", activities added on the first day are considered "Preplanned" and the activities added in the routine survey completed in the upfront interview are "Routine".

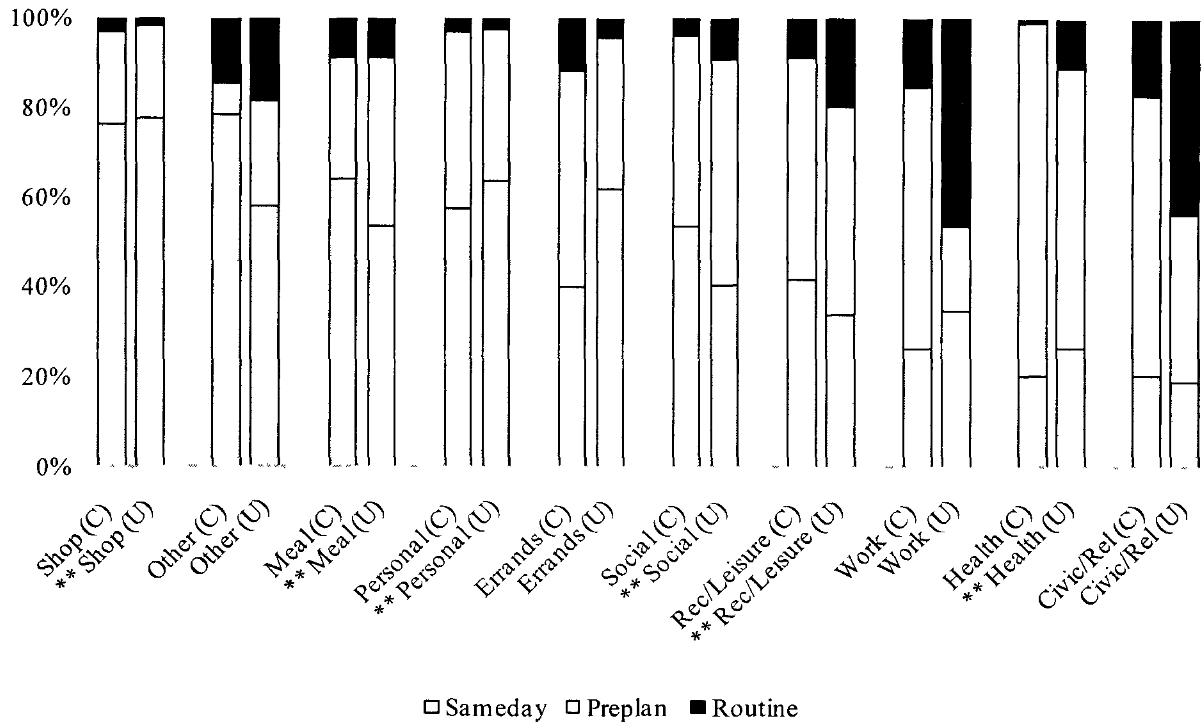
TABLE XXXII
RETROSPECTIVE VERSUS PROSPECTIVE PLAN HORIZON COMPARISON

		Retrospective			
		Same Week	**Preplan**	**Routine**	**Total**
Prospective	Same Week	23		6	29
	Preplan	2	5	5	12
	Routine	4		17	21
	Total	29	5	28	62
	% accuracy:	73%			

The results show that there was a high degree of similarity between the responses from the prospective and retrospective surveys of activity planning, with 73% accuracy of the prospective estimates to the retrospectively observed plan horizons. The differences were most pronounced for the retrospectively identified "routine" activities, where only 61% were so identified in the prospective survey. Similarly, only 5 of 12 prospectively identified "Preplanned" activities were so identified in the retrospective survey, with many of the activities classified as "routine". Fortunately, however, there is strong correspondence between the retrospective and prospective surveys in identifying planning decisions made in the same week, with 80% agreement between the results. Although these initial results are only obtained for a small sample of individuals, it does provide qualitative evidence that individuals possess a moderate ability to retrospectively estimate planning times although more study is clearly needed.

Therefore, in addition to comparing the prompted recall activity/attribute planning horizon results to the prospective estimates from the preplanning survey, it was also informative to show how the current results compare to previous activity planning horizon surveys. Because no other sources of data on individual attribute planning horizons were observed, this comparison is necessarily limited to involve only the overall activity planning horizon. For this analysis, the activity plan horizon results are compared to the plan horizons found in the CHASE© survey (Doherty et al. 2004). The CHASE survey was conducted in a similar, but much more detailed, manner as the preplanning survey previously described in Section 19.4. This survey was conducted for a one-week time period and involved collecting activity planning and scheduling results from 373 individuals (Doherty et al. 2004), with the individuals asked about the activity planning horizon whenever an activity was added to the schedule.

The comparison is shown in Figure 52, with the activity planning horizon distributions for 10 classes of out-of-home activities from both the UTRACS and CHASE surveys. The plan horizons are classified into three responses "Same Day", "Preplan" and "Routine" for clarity. The activities are sorted roughly in order of decreasing impulsiveness. The results show that there is a fairly similar trend in how activities of different types are planned between the UTRACS and CHASE survey results in terms of the activity plan horizon. Mandatory-type and scheduled activities, i.e. work, healthcare, religious services, tend to have the highest percentage of preplanned and routine episodes as expected. In contrast, maintenance-type activities: shopping, errands, personal, meals, tend to have the lowest degree of preplanning, with the obvious exception of healthcare activities, while discretionary activities fall somewhere in the middle. For six out of ten categories, there are no statistically significant differences in plan horizon distributions. The major difference between the UTRACS and CHASE results is evident from the figure, however. For the activities which are traditionally referred to as mandatory –work and to a lesser extent religious services– the UTRACS results exhibit a higher level of routinely planned activities as compared to the CHASE data. The higher level of routine healthcare and religious activities is expected for the UTRACS survey, however, due to the nature of the survey. In the CHASE survey, individuals reported one plan horizon for the entire activity, potentially leading to confusion in the case of say a work activity which occurred at a non-routine time. There is likely to be a tendency to report such an activity in CHASE as non-routine as the timing is different. However, in UTRACS the individual can report the activity as a routine activity occurring at a non-routine time as all of the individual attribute plan horizons are also recorded.



Note C = CHASE survey, U = UTRACS

Figure 52. Activity Plan Horizon by Activity Type for UTRACS and CHASE

The plan horizon distributions from UTRACS for the remaining activity types are remarkably similar to the results of the CHASE survey, considering the socio-demographic and regional differences in the samples. The six largely non-routine activity types (shopping, healthcare, personal business, social, leisure/recreation and meals) all have statistically insignificant differences based on the results of a chi-square test at the 0.05 level. This potentially shows again that the differences in the plan horizon distributions between the surveys are in the understanding of what is meant by "routine" activity. Because participants were asked to give plan horizons for both the activity and its attributes they were likely more willing to mark an activity as "routine" while not considering the individual attributes as such rather than being limited to one overall plan horizon which could potentially cause confusion about what the plan horizon refers to as observed by Doherty (2005).

23. CONCLUSIONS AND FUTURE WORK

This part of the thesis has described in detail the design, implementation and initial data analysis of the UTRACS survey, which has been used in many ways in the development of the ADAPTS activity-based model. The design of the UTRACS survey was unique in terms of prompted recall surveys using GPS in the way it handled instantaneous data processing, learning algorithms to reduce respondent burden and the inclusion of questions relating to activity planning behavior in a prompted recall survey. The implementation of UTRACS for Chicago was a successful first attempt at producing a survey of this kind.

Data was collected on the long term activity-travel behavior and planning process for 112 individuals for an average of 10 days. The data was analyzed in terms of response bias, data quality and the introduction of fatigue and conditioning, which were all topics of concern before the survey was started. The analysis showed that the response bias was acceptable, and several data quality measures such as missing values index and response rate showed that the data was of high quality compared to accepted standards (Stopher et al. 2008). The survey showed no signs of fatigue, with consistent observations throughout the survey and many of the respondents actually showing an improved ability to answer the survey questions as they learned more about it. Post-survey questioning revealed that indeed this was the case, with most respondents agreeing that the survey period was not too long. Evidence of conditioning was also not found in the analysis, with no change in the average amount of travel time or the activity distributions over the life of the survey. These results all show that the data is acceptable for use in the initial model development for various aspects of the ADAPTS model, as described in Part I of the thesis. However, it is clear that the small sample size of this initial implementation is a limiting factor in including socio-demographic attributes in many of the models, and in generalizing results from the UTRACS data.

The initial results of the survey show that the planning data obtained from the survey respondents appear to be reliable, with the data exhibiting expected patterns in regards to how attributes are planned in relation to how the overall activities are planned. The activity flexibilities also showed a clear relation to the activity plan horizon, which was further investigated in Part I of this thesis. A preliminary analysis of the activity planning order was undertaken to determine which attributes are planned first for both routine and non-routine activities. This analysis showed that there is a great diversity in how activities are planned with respondents rarely determining that all activity attributes were selected at once or in any defined sequence. The results of the planning order analysis show that only rarely are all attributes planned at once as this occurs in less than 8% of activities. Additionally, the results of this analysis show that the planning of attributes does not occur in any discernible fixed order, although some tendencies are observed, such as location and timing tend to be planned first, and the mode choice is often made first for activities with non-routine attributes. In general, however, many different activity planning order strategies are observed and so multivariate modeling techniques are needed in order to determine potential underlying patterns behind the observed activity planning order. These results have important implications for activity-based models which often model the separate attribute decisions in fixed sequences as differing conditional dependencies between attribute decisions can arise depending on the choice timing, motivating further study in this area.

In addition, the prompted recall planning responses were compared to the results of the preplanning survey for each respondent to determine how well the respondents' prospective estimates of planning horizon matched their later retrospective results. This analysis specifically focused on how often retrospectively recalled preplanned activities were found in the prospective data, since the opposite situation, i.e. prospective preplanned activities not found in the recalled data, are expected to arise naturally as a result of the rescheduling process. Overall it was found that 74% of recalled activities were actually observed prospectively, with 73% accuracy between the prospective and retrospective plan horizon response. Finally, overall activity plan horizons for different activity types where shown to be fairly similar to results obtained in a different activity scheduling survey, where the differences were mainly due to differing interpretations of what constitutes a "routine" activity. In fact 6 of the 9 overall activity types showed no statistically significant difference in plan horizon distribution, providing potentially encouraging signs of the transferability of activity planning process data.

There are many areas, besides collecting larger sample sizes, where future work on surveys of this type could lead to improvement. One prime area for potential future research is in the design of the survey questions. More work is needed on identifying the types of questions that can be asked, and which are most effective at eliciting the desired information without being overly complex or confusing to participants. In addition, attempts should be made to determine the possibility of collecting pre-planning data as in the CHASE data collection effort

(Doherty 2004) in combination with the activity-travel survey, which would give a more complete picture of the dynamics of the activity scheduling process as suggested by Doherty et al. (2001).

Beyond evaluating the actual survey design, further work is needed in identifying the ways in which data collected from such surveys can be used. One potential is to use the data collected activity location and route choice decisions to investigate the formation of mental or cognitive maps (Golledge and Garling 2004), which could greatly enhance the realism of travel choice models. If the time-frame of the survey is extended long enough, a significant portion of the common places in the persons mental map are likely to be visited. The perceptions about quality, distance, etc. relating to the route or activity locations of the individual can be compared to reality to generate models of individual's perception and mental map formation. Additionally, how the individuals learn and perceive their environment over time can also potentially be observed and the data collected can contribute to modeling of these processes. Knowledge gained during studies of these various processes can then be fed back to improve the overall survey design.

While it is clear that much work remains in developing and validating long-term prompted recall surveys using GPS data collection methods, the survey described in this thesis represents an important advance in personal travel surveying and activity planning data collection. Data collection efforts of the type described here should help to further improve knowledge of the dynamics of household activity and travel decisions, and enable more realistic models of activity-travel demand.

CITED LITERATURE

Agrawal, R and Srikant, R (1995) Mining sequential patterns, *Eleventh International Conference on Data Engineering*, Yu, P S & Chen, A S P (ed), IEEE Computer Society Press, 1995, *3-14*

Agrawal, R , Imielinski, T & Swami (1993) A Mining association rules between sets of items in large databases, *SIGMOD Rec* , ACM Press, 1993, 22, *207-216*

Arentze, T A & Timmermans, H J P (2005) Representing mental maps and cognitive learning in micro-simulation models of activity-travel choice dynamics *Transportation*, 32, *321 – 34*

Arentze, T and H Timmemans (2000) ALBATROSS – A Learning Based Transportation Oriented Simulation System European Institute of Retailing and Services Studies (EIRASS), Technical University of Eindhoven

Ashbrook, D and T Starner (2003) Using GPS to learn significant locations and predict movement across multiple users *Personal and Ubiquitous Computing*, 7, 275-286

Axhausen, K W , A Zimmermann, S Schonfelder, G Rindsfüser and T Haupt (2002) Observing the rythms of daily life A six-week travel diary, *Transportation*, 29, 95-124

Axhausen, K W , S Schonfelder, J Wolf, M Oliveira and U Samaga (2004) Eighty Weeks of GPS Traces Approaches to Enriching Trip Information *Proceedings of the 83^{th} Annual Meeting of the Transportation Research Board*, January 2004 Washington, D C

Axhausen, K W , M Lochel, R Schulich, T Buhl and P Widmer (2007) Fatigue in long-duration travel diaries Transportation, Vol 34, Springer, Netherlands,143-160

Battelle Transport Division (1997) *Lexington Area Travel Data Collection Test*, Final report prepared for the FHWA

Bricka, S and C R Bhat (2006) Comparative Analysis of GPS-Based and Travel Survey-Based Data *Transportation Research Record Journal of the Trans-portation Research Board*, 1972, 9-20

Cambridge Systematics (2007) *PSRC 2006 Household Activity Survey Analysis Report Final Report* Puget Sound Regional Council, April 2007

Casas J and C Arce (2003) Trip Reporting in Household Travel Diaries A Comparison to GPS-Collected Data *Proceedings of the 78^{th} Annual Meeting of the Transportation Research Board*, January 1999 Washington, D C

Chung, E-H and A S Shalaby (2005) Development of a Trip Reconstruction Tool for GPS-Based Personal Travel Surveys *Journal of Transportation Planning and Technology 28 (5), 381-401*

Clark, A F and S T Doherty (2008) Examining the Nature and Extent of the Activity-travel Preplanning Decision Process Proceedings of the 87th Annual Meeting of the Transportation Research Board, January 2008

Doherty, S , Noel, N , Gosselin, M , Sirois, C & Ueno, M (2001) Moving Beyond Observed Outcomes – Integrating Global Positioning Systems and Interactive Computer-Based Travel Behavior Surveys *Transportation Research E-Circular E-C026*, March 2001

Doherty, S T , E Nemeth, M Roorda and E J Miller (2004) Design and Assessment of the Toronto Area Computerized Household Activity Scheduling Survey *Transportation Research Record Journal of the Transportation Research Board,* 1894, 140-149

Doherty, S T (2005) How Far in Advance are Activities Planned? Measurement Challenges and Analysis *Transportation Research Record Journal of the Trans-portation Research Board*, 1926, 41-49

Doherty, S T and E J Miller (2000) A computerized household activity scheduling survey *Transportation* 27, 75-97

Draijer, G , N Kalfs and J Perdok (2000) Global Positioning System as Data Collection Method for Travel Research *Transportation Research Record Journal of the Trans-portation Research Board*, 1719, 147-153

Du, J and L Aultman-Hall (2007) Increasing the accuracy of trip rate information from passive multi-day GPS travel datasets Automatic trip end identification issues *Transportation Research Part A 41, 220-232*

Ericsson, K A and R J Crusher (1991) Introspection and Verbal Reports on Cognitive Processes-Two Approaches to the Study of Thinking A Response to Howe* New Ideas in Psychology, 9 (1), 57-71

Ericsson, K A , & Simon, H A (1993) Protocol Analysis Verbal Reports as Data Cambridge, MA MIT Press

Flamm, M , C Jemelin and V Kaufmann (2007) Combining person based GPS tracking and prompted recall interviews for a comprehensive investigation of travel behaviour adaptation processes during life course transitions *Proceedings of the 7th Swiss Transport Research Conference*, September 2007, Monte Verita, Switzerland

Forrest, T and D Pearson (2005) Comparison of trip determination methods in household travel surveys enhanced by GPS *Transportation Research Record Journal of the Transportation Research Board,* 1917, 63-71

Frignani, M J A Auld, A Mohammadian, C Williams and P Nelson (2010) Urban Travel Route and Activity Choice Survey (UTRACS) An Internet-Based Prompted Recall Activity Travel Survey using GPS Data Proceedings of the 89th Annual Meeting of the Transportation Research Board (DVD), January 2010, Washington, D C

Garling, T , M -P Kwan and R G Golledge (1994) Computational-process modeling of household travel activity scheduling Transportation Research B 25, 355-364

Golledge, R G and T Garling (2004) Cognitive Maps and Urban Travel, in D A Hensher, K J Button, K E Haynes and P R Stopher, eds, *Handbook of Transport Geography and Spatial Systems* Oxford Elsevier

Guensler, R and J Wolf (1999) Development of a Handheld Electronic Travel Diary for Monitoring Individual Tripmaking Behavior *Proceedings of the 78th Annual Meeting of the Transportation Research Board*, January 1999 Washington, D C

Hackney, J F Marchal and K Axhausen (2005) Monitoring a road system's level of service The Canton Zurich floating car study 2003, *Proceedings of the 84th Annual Meeting of the Transportation Research Board*, January 2005 Washington, D C

Hallmark, S L (2004) Other Transportation Applications of GPS, in D A Hensher, K J Button, K E Haynes and P R Stopher, eds, *Handbook of Transport Geography and Spatial Systems* Oxford Elsevier

Hayes-Roth, B and F Hayes-Roth (1979) A cognitive model of planning Cognitive Science 3, 275-310

Jan, O , A J Horowitz and Z-R Peng (2000) Using Global Positioning System Data to Understand Variations in Path Choice *Transportation Research Record Journal of the Transportation Research Board,* 1725, 37-44

Lee, M S and McNally,M G (2001) Experiments with A Computerized Self-Administered Activity Survey, Transportation Research Record Journal of the Transportation Research Board, 1752, 91-99

Lee, M S and McNally, M G (2003) On the structure of weekly activity/travel patterns *Transportation Research Part A Policy and Practice*, 2003, 37, *823-839*

Lee-Gosselin, M E , S T Doherty and D Papinski (2006) An Internet-based Prompted Recall Diary with Automated GPS Activity-trip Detection System Design *Proceedings of the 85th Annual Meeting of the Transportation Research Board*, January 2006 Washington, D C

Li, H , R Guensler and J Ogle (2005) An Analysis of Morning Commute Route Choice Patterns Using GPS Based Vehicle Activity Data *Proceedings of the 84th Annual Meeting of the Transportation Research Board*, January 2005 Washington, D C

Li, Z J and A S Shalaby (2008) Web-based GIS System for Prompted Recall of GPS-assisted Personal Travel Surveys System Development and Experimental Study *Proceedings of the 87th Annual Meeting of the Transportation Research Board*, January 2008 Washington, D C

Liao, L , Fox, D & Kautz, H (2004) Learning and Inferring Transportation Routines *Proceedings of the Nineteenth National Conference on Artificial Intelligence*, 2004, *348-353*

Madre, J -L , K W Axhausen and W Brog (2007) Immobility in travel diary surveys *Transportation*, Vol 34, 107-128

Marca, J E (2002) *The Design and Implementation of an On-Line Travel and Activity Survey* Center for Activity Systems Analysis Paper UCI-ITS-AS-WP-02-1 http //repositories cdlib org/itsirvine/casa/UCI-ITS-AS-WP-02-1

Marca, J E , C R Rindt and M G McNally (2002) *Collecting Activity Data from GPS Readings* Center for Activity Systems Analysis Paper UCI-ITS-AS-WP-02-3 http //repositories cdlib org/itsirvine/casa/UCI-ITS-AS-WP-02-3

McGowen, P and M McNally (2007) Evaluating the Potential to Predict Activity Types from GPS and GIS Data *Proceedings of the 86th Annual Meeting of the Transportation Research Board*, January 2007 Washington, D C

Miller, E J (2005) Propositions for Modelling Household Decision-Making, in Integrated Land-use and Transportation Models Behavioural Foundations, M Lee-Gosselin and S T Doherty (eds), Oxford Elsevier, pp 21-60

Mohammadian, K , Rashidi, T , Takuriah, P (2009) Effectiveness of transit strategies targeting elderly people Survey results and preliminary data analysis Research report FHWA-ICT-09-033, a report of the findings of the project ICT-R27-17 Illinois Center for Transportation

Murakami, E and D P Wagner (1999) Can using global positioning system (GPS) improve trip reporting? *Transportation Research Part C 7 149-165*

Murakami, E , J Morris and C Arce (2003) Using Technology to Improve Tranport Survey Quality *Transport Survey Quality and Information* Elsevier, Oxford

Nisbett, R E , DeCamp Wilson, T , 1977 Telling more than we can know verbal reports on mental processes Psychological Review, 84, 231-259

NuStats (2002) *2000-2001 California Statewide Household Travel Survey Final Report* California Department of Transportation June 2002

NuStats (2004) *Kansas City Regional Household Travel Survey GPS Study Final Report* Mid-America Regional Council, June 2004

Papinski, D , D M Scott and S T Doherty (2008) Exploring the route choice decision-making process A comparison of pre-planned and observed routes obtained using person-based GPS *Proceedings of the 87th Annual Meeting of the Transportation Research Board*, January 2008 Washington, D C

Pierce, B , J Casas and G Giaimo (2003) Estimating Trip Rate Under-Reporting Preliminary Results from the Ohio Household Travel Survey *Proceedings of the 82th Annual Meeting of the Transportation Research Board*, January 2003 Washington, D C

Přibyl, O & Goulias, K G (2005) Simulation of Daily Activity Patterns Incorporating Interactions Within Households Algorithm Overview and Performance *Transportation Research Record Journal of the Transportation Research Board*, 1926, 135-141

Quiroga, C (2004) Traffic Monitoring Using GPS, in D A Hensher, K J Button, K E Haynes and P R Stopher, eds, *Handbook of Transport Geography and Spatial Systems* Oxford Elsevier

Rindsfüser, G , H Muhlhans, S T Doherty, K J Beckmann (2003) Tracing the planning and execution of activities and their attributes - design and application of a hand-held scheduling process survey Proceedings of the 10th International Conference on Travel Behaviour Research, Lucerne, Switzerland

Roorda, M J , S T Doherty and E J Miller (2005) Operationalising Household Activity Scheduling Models Addressing Assumptions and the Use of New Sources of Behavioral Data Integrated Land-use and Transportation Models Behavioural Foundations, M Lee-Gosselin and S T Doherty (eds), Oxford Elsevier, pp 61-85

Ruiz, T and H Timmermans (2006) Changing the Timing of Activities in Resolving Scheduling Conflicts Transportation 33, 429-445

Schonfelder, S , K W Axhausen, N Antille and M Bierlaire (2002) Exploring the potentials of automatically collected GPS data for travel behaviour analysis A Swedish data source, in J Moltgen and A Wytzisk, eds GITechnologien für Verkehr und Logistik, IfGIprints, 13, 155-179

Srinivasan, S , P Ghosh, A Sivakumar, A Kapur, C R Bhat and Stacey Bricka (2006) *Conversion of Volunteer-Collected GPS Diary Data into Travel Time Performance Measures Final Report* Center for Transportation Research at The University of Texas at Austin, February 2006

Stopher, P and A Collins (2005) Conducting a GPS Prompted Recall Survey over the Internet *Proceedings of the 84th Annual Meeting of the Transportation Research Board*, January 2005 Washington, D C

Stopher, P P Bullock and F Horst (2002) *Exploring the Use of Passve GPS Devices to Measure Travel* Institute of Transport and Logistics Studies, Paper ITLS-WP-02-06, University of Sydney

Stopher, P , C FitzGerald and J Zhang (2006a) *Advances in GPS Technology for Measuring Travel* Institute of Transport and Logistics Studies, Paper ITLS-WP-06-15, University of Sydney

Stopher, P , C FitzGerald and T Biddle (2006b) *Pilot Testing a GPS Panel for Evaluating TravelSmart®* Institute of Transport and Logistics Studies, Paper ITLS-WP-06-16, University of Sydney

Stopher, P R , N Swann, and C FitzGerald (2007a) *Using an Odometer and a GPS Panel to Evaluate Travel Behaviour Changes*, paper presented to the 11th TRB National Planning Applications Conference, Daytona Beach, FL, May 2007

Stopher, P R et al (2007b) Technical Appendix to NCHRP Report 571 Standardized Procedures for Personal Travel Surveys Transportation Research Board of the National Academies, Washington, D C

Stopher, P R et al (2008) Standardized procedures for personal travel surveys National Cooperative Highway Research Program report 571 Transportation Research Board of the National Academies, Washington, D C

Tsui, S Y A and A S Shalaby (2006) An Enhanced System for Link and Mode Identification for GPS-based Personal Travel Surveys *Transportation Research Record Journal of the Transportation Research Board*, 1972, 38-45

Wolf, J (2000) *Using GPS Data Loggers to Replace Travel Diaries in the Collection of Travel Data* Dissertation, Georgia Institute of Technology, School of Civil and Environmental Engineering, Atlanta, Georgia, July 2000

Wolf, J (2004) Defining GPS and its Capabilities, in D A Hensher, K J Button, K E Haynes and P R Stopher, eds, *Handbook of Transport Geography and Spatial Systems* Oxford Elsevier

Wolf, J , R Guensler, L Frank and J Ogle (2000) The Use of Electronic Travel Diaries and Vehicle Instrumentation Packages in the Year 2000 Atlanta Regional Household Travel Survey Test Results, Package Configurations, and Deployment Plans *Proceedings of the 9th International Association of Travel Behavior Research Conference*, July 2000, Queensland, Australia

Wolf, J , R Guensler and W Bachman (2001) Elimination of the Travel Diary An Experiment to Derive Trip Purpose From GPS Travel Data *Proceedings of the 80th Annual Meeting of the Transportation Research Board*, January 2001 Washington, D C

Wolf, J , S Bricka, T Ashby and C Gorugantua (2004) *Advances in the Application of GPS to Household Travel Surveys* Presented at the Transportation Research Board National Household Transportation Survey Conference, Washington D C

Zmud, J and J Wolf (2003) Identifying the Correlates of Trip Misreporting - Results from the California Statewide Household Travel Survey GPS Study *Proceedings of the 10th International Conference on Travel Behaviour Research*, August 2003, Lucerne, Switzerland

APPENDIX

University of Illinois
at Chicago

Office for the Protection of Research Subjects (OPRS)
Office of the Vice Chancellor for Research (MC 672)
203 Administrative Office Building
1737 West Polk Street
Chicago, Illinois 60612-7227

Exemption Granted

December 1, 2008

Abolfazl Mohammadian, Ph.D.
Civil and Materials Engineering
842 W Taylor Street
M/C 246
Chicago, IL 60607
Phone: (312) 996-9840 / Fax: (312) 996-2426

RE: Research Protocol # 2008-1005
"Prompted Recall GPS Survey of the Activity-Travel Patterns of the Elderly"

Sponsor:	Illinois Department of Transportation
PAF#	2008-06141
Grant Contract No	D7688
Grant Contract Title	Seniors Trip Chaining Behavior

Dear Dr. Mohammadian:

Your Claim of Exemption was reviewed on November 26, 2008 and it was determined that your research protocol meets the criteria for exemption as defined in the U. S. Department of Health and Human Services Regulations for the Protection of Human Subjects [(45 CFR 46.101(b)]. You may now begin your research.

Exemption Period: **November 26, 2008 – November 25, 2011**

Your research may be conducted at UIC and with adult subjects only.

The specific exemption category under 45 CFR 46.101(b) is:

(2) Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior, unless: (i) information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

You are reminded that investigators whose research involving human subjects is determined to be exempt from the federal regulations for the protection of human subjects still have responsibilities for the ethical conduct of the research under state law and UIC policy. Please be aware of the following UIC policies and responsibilities for investigators.

1. Amendments You are responsible for reporting any amendments to your research protocol that may affect the determination of the exemption and may result in your research no longer being eligible for the exemption that has been granted.

2. Record Keeping You are responsible for maintaining a copy all research related records in a secure location in the event future verification is necessary, at a minimum these documents include: the research protocol, the claim of exemption application, all questionnaires, survey instruments, interview questions and/or data collection instruments associated with this research protocol, recruiting or advertising materials, any consent forms or information sheets given to subjects, or any other pertinent documents.

3. Final Report When you have completed work on your research protocol, you should submit a final report to the Office for Protection of Research Subjects (OPRS).

4. Information for Human Subjects UIC Policy requires investigators to provide information about the research protocol to subjects and to obtain their permission prior to their participating in the research. The information about the research protocol should be presented to subjects in writing or orally from a written script. When appropriate, the following information must be provided to all research subjects participating in exempt studies:
   a. The researchers affiliation; UIC, JBVMAC or other institutions,
   b. The purpose of the research,
   c. The extent of the subject's involvement and an explanation of the procedures to be followed,
   d. Whether the information being collected will be used for any purposes other than the proposed research,
   e. A description of the procedures to protect the privacy of subjects and the confidentiality of the research information and data,
   f. Description of any reasonable foreseeable risks,
   g. Description of anticipated benefit,
   h. A statement that participation is voluntary and subjects can refuse to participate or can stop at any time,
   i. A statement that the researcher is available to answer any questions that the subject may have and which includes the name and phone number of the investigator(s).
   j. A statement that the UIC IRB/OPRS or JBVMAC Patient Advocate Office is available if there are questions about subject's rights, which includes the appropriate phone numbers.

Please be sure to:

→Use your research protocol number (listed above) on any documents or correspondence with the IRB concerning your research protocol.

We wish you the best as you conduct your research. If you have any questions or need further help, please contact me at (312) 355-2908 or the OPRS office at (312) 996-1711. Please send any correspondence about this protocol to OPRS at 203 AOB, M/C 672.

Sincerely,

Charles W. Hoehne
Assistant Director, IRB # 2
Office for the Protection of Research Subjects

Enclosure(s): None

cc: Farhad Ansari, Civil and Materials Engineering, M/C 246

VITA

NAME	Joshua Allen Auld
EDUCATION	B S , Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 2002
	M S , Civil and Materials Engineering, University of Illinois at Chicago, 2007
	Ph D , Civil and Materials Engineering, University of Illinois at Chicago, 2011
RESEARCH	United States Department of Energy, Transportation Engineer, Argonne National Laboratory, Lemont, Illinois, 2011
	Department of Civil and Materials Engineering, Graduate Research Fellow, University of Illinois at Chicago, Chicago, Illinois, 2008 – 2010
	Department of Civil and Materials Engineering, Graduate Research Assistant, University of Illinois at Chicago, Chicago, Illinois, 2007 – 2011
TEACHING	Department of Civil and Materials Engineering, University of Illinois at Chicago, Geometric Design of Highway Facilities, 2007
	Department of Civil and Materials Engineering, University of Illinois at Chicago, Traffic Engineering and Design, 2010
HONORS	National Science Foundation Integrative Graduate Education and Research Traineeship Fellowship, University of Illinois at Chicago, 2008 – 2010
PROFESSIONAL MEMBERSHIP	American Society of Civil Engineers Institute of Transportation Engineers International Association of Travel Behavior Research International Association of Time Use Research World Conference on Transport Research Societ
PUBLICATIONS	Auld, J A and A Mohammadian (2011) Constrained Destination Choice in the ADAPTS Activity-Based Model Forthcoming in Transportation Research Record Journal of the Transportation Research Board
	Auld, J A , T Rashidi, M Javanmardi and A Mohammadian (2011) Activity Generation Model Using a Competing Hazard Formulation Forthcoming in Transportation Research Record Journal of the Transportation Research Board
	Auld, J A and A Mohammadian (2011) Empirical Analysis of the Activity Planning Process Forthcoming in Transportation Research Record Journal of the Transportation Research Board
	Frignani, M , J A Auld and A Mohammadian (2011) Empirical Analysis of the Decision-Making and Tour Formation Process Comparison between Seniors and Younger Individuals Forthcoming in Transportation Research Record Journal of the Transportation Research Board

VITA (continued)

PUBLICATIONS:

Auld, J.A. and A. Mohammadian (2010). An Efficient Methodology for Generating Synthetic Populations with Multiple Control Levels. Transportation Research Record: Journal of the Transportation Research Board, 2175, 138-147.

Frignani, M., J.A. Auld, A. Mohammadian, C. Williams and P. Nelson (2010). Urban Travel Route and Activity Choice Survey (UTRACS): An Internet-Based Prompted Recall Activity Travel Survey using GPS Data. Transportation Research Record: Journal of the Transportation Research Board, 2183, 19-28.

Auld, J.A., A. Mohammadian and M.J. Roorda (2009). Implementation of a Scheduling Conflict Resolution Model in an Activity Scheduling System. Transportation Research Record: Journal of the Transportation Research Board. 2135, 96-105.

Auld, J.A. and A. Mohammadian (2009). Framework for the Development of the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) Model. Transportation Letters, International Journal of Transportation Research, 1 (3), 245-255.

Auld, J.A., A. Mohammadian and K. Wies (2009). Population Synthesis with Region-Level Control Variable Aggregation. Journal of Transportation Engineering, 135 (9), 632-639.

Auld, J.A., A. Mohammadian and S.T. Doherty (2009). Modeling Activity Conflict Resolution Strategies Using Scheduling Process Data. Transportation Research Part A: Policy and Practice, 43 (4), 386-400.

Auld, J. A., C. Williams, A. Mohammadian and P. Nelson (2009). An Automated GPS-Based Prompted Recall Survey with Learning Algorithms. Transportation Letters, International Journal of Transportation Research, 1 (1), 59-79.

Auld, J.A., A. Mohammadian and S.T. Doherty (2008). Analysis of Activity Conflict Resolution Strategies. Transportation Research Record: Journal of the Transportation Research Board. 2054, 10-19.

July 14, 2011

Martina Frignani
2201 Severn Ave. Apt. F103
Metairie, LA 70001

Dear Martina:

I am writing to request permission to use material from your publication – *Urban Travel Route and Activity Choice Survey (UTRACS): An Internet-Based Prompted Recall Activity Travel Survey using GPS Data*,Tr ansportation Research Record, 2183, 2010 – in my thesis. The sections on recruitment and data validation are being incorporated as Chapter 21 of my thesis with minor variation. Unless you request otherwise, I will use the conventional style of the Graduate College of the University of Illinois at Chicago as acknowledgment.

A copy of this letter is included for your records. Thank you for your kind consideration of this request.

Sincerely,

Joshua A. Auld
6945 167th St.
Tinley Park, IL 60477

The above request is approved.

Approved by:____ Date: 7/15/2011

July 14, 2011

Dr. Taha Hossein Rashidi
60 St. Patrick St. Apt 926
Toronto, On, M5T-7X5

Dear Dr. Rashidi:

I am writing to request permission to use material from our joint publication – *Activity Generation Model Using a Competing Hazard Formulation*, to be published in Transportation Research Record, 2011 – in my thesis. The sections on hazard model background and model formulation are being incorporated into Chapter 8, Sections 1 and 2 of my thesis with minor variations. Unless you request otherwise, I will use the conventional style of the Graduate College of the University of Illinois at Chicago as acknowledgment.

A copy of this letter is included for your records. Thank you for your kind consideration of this request.

Sincerely,

Joshua A. Auld
6945 167th St.
Tinley Park, IL 60477

The above request is approved.

Approved by:_______________Taha Hossein Rashidi__ Date: __07/17/11____

Taha Hossein Rashidi

July 14, 2011

Martina Frignani
2201 Severn Ave. Apt. F103
Metairie, LA 70001

Dear Martina:

I am writing to request permission to use material from your publication – *Urban Travel Route and Activity Choice Survey (UTRACS): An Internet-Based Prompted Recall Activity Travel Survey using GPS Data*,Tr ansportation Research Record, 2183, 2010 – in my thesis. The sections on recruitment and data validation are being incorporated as Chapter 21 of my thesis with minor variation. Unless you request otherwise, I will use the conventional style of the Graduate College of the University of Illinois at Chicago as acknowledgment.

A copy of this letter is included for your records. Thank you for your kind consideration of this request.

Sincerely,

Joshua A. Auld
6945 167th St.
Tinley Park, IL 60477

The above request is approved.

Approved by:____ Date: 7/15/2011

July 14, 2011

Dr. Taha Hossein Rashidi
60 St. Patrick St. Apt 926
Toronto, On, M5T-7X5

Dear Dr. Rashidi:

I am writing to request permission to use material from our joint publication – *Activity Generation Model Using a Competing Hazard Formulation*, to be published in Transportation Research Record, 2011 – in my thesis. The sections on hazard model background and model formulation are being incorporated into Chapter 8, Sections 1 and 2 of my thesis with minor variations. Unless you request otherwise, I will use the conventional style of the Graduate College of the University of Illinois at Chicago as acknowledgment.

A copy of this letter is included for your records. Thank you for your kind consideration of this request.

Sincerely,

Joshua A. Auld
6945 167th St.
Tinley Park, IL 60477

The above request is approved.

Approved by:_______________Taha Hossein Rashidi__ Date: __07/17/11____

Taha Hossein Rashidi