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Incorporating Individual Activity Arrival and Duration Preferences within a Time-of-day Travel Disutility Formulation of the Household Activity Pattern Problem (HAPP)

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil Engineering

by

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2014

DEDICATION

To

my family

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I would like to express the deepest appreciation to my committee chair Professor Will Recker for advising me and guiding me through the completion of this dissertation. It was my great fortune that my advisor was one of the pioneers of activity-based demand modeling. Without his guidance and persistent help this dissertation would not have been possible. There were many occasions where found myself struggling with implementing the HAPP model and Professor Recker was always available to push me past these obstacles. I would like to thank Professor Joseph Chow for the initial discussions about a dynamic HAPP model that eventually led to the traffic-dependent HAPP model developed in my dissertation. I would also like to thank my committee members, Professor Michael G. McNally and Professor R. Jayakrishnan for the many discussions on activity-based demand models during the early stages of my dissertation work. I would like to thank Professor Robert Fourer for answering my questions about coding in AMPL. Through his online discussion group I was able to ask numerous questions regarding AMPL and he always provided helpful and thoughtful responses. I would like to thank Sarah Hernandez for helping with edits to my dissertation and continued discussion on my research. I would like to thank Qijian Gan for his guidance on the particulars of coding in Matlab. I would like to thank Hsi-Hwa Hu, Hao Cheng, Yongping Zhang, Mana Sangkapichai and other staff at SCAG for their insights into developing practice oriented activity-based models. My valuable experience as an intern at SCAG opened my eyes to the current and future obstacles faced in regional transportation planning and modeling. This dissertation came to fruition as a result of my complementary experiences in the transportation research and practice arenas. This dissertation represents a connection between HAPP as a research product and an implementable tool used in practice. I hope this dissertation can narrow that common gap that exists in so many research areas by guiding valuable research products into practice. More than anything, I would like to thank my parents for supporting me through my PhD studies. Without their continued support, I would not have been able to pursue my PhD and their help tremendously alleviated the stresses of everyday life.

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ABSTRACT OF THE DISSERTATION

Incorporating Individual Activity Arrival and Duration Preferences within a Time-of-day Travel Disutility Formulation of the Household Activity Pattern Problem (HAPP)

By

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Doctor of Philosophy in Civil Engineering

University of California, Irvine, 2014

Professor Will Recker, Chair

This dissertation provides modifications and extensions to the Household Activity Pattern Problem (HAPP) to help move existing formulations from a laboratory prototype toward a more useable activity-based demand modeling product. Previous research on HAPP has been based on a pickup and delivery problem with time window constraints (PDPTW), which does not lend itself easily to application that is compatible with an activity-based forecasting model. Meanwhile, other research on activity-based modeling lacks of the integration of household decisions regarding time-of-day arrival, activity duration and traffic congestion effects on travel. We borrow concepts from economic research and consider that each household member tries to obtain maximum utility by choosing arrival time of activities, choosing activity duration while minimizing travel times and travel costs throughout the course of the day. Chapter 1 provides the introduction and motivation of this research. Chapter 2 reviews pertinent literature relative to the activity-based approach, the HAPP model, and positions the dissertation research relative to the

existing state-of-the-art. In Chapter 3 we propose extensions to HAPP (UHAPP) that incorporate time of day activity arrival utility and the utility of activity duration into HAPP as decision variables. In Chapter 4 we introduce the travel time-dependent household activity pattern problem model (TUHAPP), which extends the ability of HAPP to capture the time-of-day (TOD) difference in travel times and costs. In Chapter 5 we develop a framework using TUHAPP (UHAPP) as a regional activity-based demand model with a household travel survey. Chapter 6 provides conclusions and future research.

Chapter 1 INTRODUCTION AND RESEARCH MOTIVATION

The foundation of activity-based travel models (ABM) is that travel demand derives from people's needs and desires to participate in activities where in many cases are located outside their homes, resulting in the need to travel. Most activity-based models are based on economic consumer behavioral theories about making decisions on activity participation in the presence of constraints, including decisions on where to participate in activities, when to participate in activities, how to get to these activities, and how long to stay at these activities. Because they represent decisions at the level of individual persons, and replicate the agenda of these people across the entire day, activity-based models are often better at representing how investments, policies, or other changes will impact people's travel behavior comparing to the trip-based four-step model, where the traditional transportation planning is typically based. Transportation planning in the US (Davidson, et al., 2007) and some developed countries in the world has changed from 'build and supply' to policy-oriented development. This change has in turn spurred a change in the methodology that forms the basis of the transportation planning process. The trip-based four-step model estimates aggregated zone to zone trips that result from the supply of facilities. As the 'build and supply' policy is not in favor after enactment of several laws, such as the Clean Air Act Amendments of 1990 (CAAA) (Clean Air Act Amendments of 1990, 1990), the Transportation Equity Act for the 21st Century (TEA-21) (TEA-21 - Transportation Equity Act for the 21st Century, 1998), the Moving Ahead for Progress in the 21st Century Act (MAP-21) (Moving Ahead for Progress in the 21st Century Act (MAP-21), 2012), the Senate Bill 375 (Senate Bill No. 375, 2008) in California, and the theoretical advantage of ABMs, many metropolitan planning organizations (MPOs) are either developing or are transitioning from the traditional trip-based four-step model to a process incorporating an activity-based demand model. In the past 40 years, activity-based demand modeling has evolved from a theoretical framework to a number of practical demand modeling packages, such as CEMDAP, FAMOS, ALBATROSS, TASHA (Pinjari & Bhat, 2011). There are two main approaches to the current state of activity-based demand modeling (Pinjari & Bhat, 2011): "utility maximization-based econometric model systems, and rule-based computational process model systems". The former approach is widely used in today's ABM modeling by many Metropolitan planning organizations (MPO), such as Portland METRO, San Francisco SFCTA, New York NYMTC, Columbus MORPC, Sacramento SACOG, Atlanta ARC, Southern California SCAG, etc.

This dissertation provides extensions to the Household Activity Pattern Problem (HAPP) (Recker W. W., 1995) to help move existing formulations from a laboratory prototype toward a more useable activity-based demand modeling product. Among the activity-based demand approaches currently available, HAPP has the advantage of a consistent internal structure that captures an individual's simultaneous decision of activity chaining, scheduling and activity people/vehicle assignment. However, there are several limitations in using HAPP as a basis for an activity-based demand modeling approach. Although the original HAPP can estimate or predict activity chaining, scheduling and ride sharing option, it treats travel times and travel costs as constant throughout the day under hard time window constraints. Moreover, its objective is based solely on travel time considerations (disutility) and ignores the actual utility gained from activity performance. Thus, it cannot reflect the arrival time preference of different people for different activities, nor the trade-offs between these preferences and adjustments to the duration of activities. Furthermore, it is not clear whether the hard time window constraints, a required input to the model, reflect boundaries on the person's preference or are only the business hours of the restaurants or stores. Not only do the hard time window constraints not reflect of the reality of people's travel outcomes, nor is activity duration a fixed, rigid constant—the duration of most activities is a decision variable that may reflect changes in the transportation facility and policies. Because a constant travel time and a constant travel cost do not reflect the reality of the traffic conditions for many people, HAPP cannot capture people's travel decision responses to changes in traffic conditions during a day. Thus, it cannot evaluate policies that regulate time-of-day traffic conditions, e.g., congestion. Based on the aforementioned limitations of HAPP, we first propose modifications and extensions to HAPP in chapter 3, presenting UHAPP, which incorporates activity utility specifications in the form of both an arrival time preference triangular demand function to address the limitation imposed by using hard time window constraints and an activity duration utility function to release the constant activity duration and, instead, treat activity duration as a decision variable. In chapter 4, we further extend UHAPP as TUHAPP to be capable of reflecting time-of-day traffic conditions on people's travel decisions. In chapter 5, we develop a framework for using TUHAPP (UHAPP) as an activity-based demand forecasting model, using household travel survey data, and present example results. We present conclusions and future research in chapter 6 where we point out the limitation of the TUHAPP and propose several ideas for addressing them.

Chapter 2 LITERATURE REVIEW

In this chapter we present the state-of-the-art in activity-based modeling and the limitations of current activity-based models and, in particular, the limitations of the HAPP model.

Literature in activity-based demand modeling

Activity-based demand modeling (ABM) can be traced back to the original work by Hägerstrand (Hägerstraand, 1970) in which regional science disaggregate individuals in terms of facing three large aggregations of constraints: 'capability constraints,' 'coupling constraints,' and 'authority constraints.' The individual movement through time-space was viewed as a prism. The demand for travel was derived from the demand for activities, which was associated with space and time constraints. Jones et al. (Jones, Dix, Clarke, & Heggie, 1983) provided a comprehensive study on better understanding of household travel behavior and initial attempts to model complex travel behavior under the activity-based demand model framework were first completed. The first operational activity-based model, STARCHILD (Recker, McNally, & Root, 1985) (Recker, McNally, & Root., 1986a) (Recker, McNally, & Root., 1986b), was designed for research purposes and it required data that were not usually available, so it was not suitable for general application.

Bowman and Ben-Akiva (Bowman & Ben-Akiva, 2001) presented an integrated activity-based discrete choice model system of an individual's activity and travel schedule, and used a 1991 Boston travel survey and transportation system level of service data to demonstrate the prototype concept. A person's choice of activities and associated travel were modeled using a nested logit model. In the prototype, the activity pattern includes: (a) the primary – most important – activity of the day, with one alternative being to remain at home for all of the day's activities; (b) the type of tour for the primary activity, including the number, purpose and sequence of activity stops; and (c) the number and purpose of secondary – additional – tours. Tour models included the choice of time of day, destination and mode of travel, and were conditioned by the choice of activity pattern. The choice of activity pattern was influenced by the expected maximum utility derived from the available tour alternatives. The principal limitation of this model system was that the level of service data used were not sufficiently accurate for a disaggregate activity-based model. Consequently, the time-of-day models were not accurate, and more detailed time-of-day travel times and costs data were required to get an acceptably accurate estimation. Also, due to the inherent limitation of discrete choice models to have a countable (small) set of alternative choices, coarse classification and choice dimensions were introduced to the model. This limited the advantage of activity-based model as a disaggregate forecast model to better evaluate different alternatives.

ALBATROSS: A Learning-based Transportation Oriented Simulation system (ALBATROSS) was developed by Arentze and Timmermans (Arentze & Timmermans, 2004) simulated individual's decisions related to each facet of activity schedules generally considered relevant for activity-travel analysis. The facets included: activity type, duration, travel party, start time, trip type, location and transport mode. The system was designed as a rule-based model in which situational, household, institutional and space–time constraints as well as choice heuristics of individuals were explicitly represented in the system. Although ALBATROSS was a comprehensive set of choice heuristics of individual's travel and scheduling decisions, it was still lacking the ability of modeling household members' joint decision making and personal interaction relationships, activity scheduling and in-home versus out-of-home activity substitution choice behavior.

Arentze and Timmermans (Arentze & Timmermans, 2004) also introduced a multi-state supernetwork approach to model multi-activity, multimodal trip chains. Their approach extended the least-cost path methods to model complete trip chains that might involve multiple transport modes and multiple activities. The results could generate an optimal sequence of traveling, transferring, parking, conducting activities and dropping off activities. Liao et al. (Liao, Arentze, & Timmermans, 2013) extended such an approach to incorporate space-time constraints in a way that the multi-state supernetworks were time-dependent, and allowed modeling choice of mode, route, parking and activity locations in a simultaneous and time-dependent manner and more accurately capturing interdependences of the activity-travel trip chaining. However, this approach did not consider interaction within a household and the illustration example was too simple to draw broad conclusions.

TASHA: the Toronto Area Scheduling for Household Agents (TASHA) (Miller & Roorda, 2003) was a prototype activity scheduling microsimulation model that generated activity schedules and travel patterns for a 24-hour typical weekday for each person within a household. The prototype model was developed based on conventional trip diary data and therefore it was easier to transfer to other areas for which conventional trip diary data were already available. The model made use of the concept of the “project,” which was defined as a coordinated set of activities tied together by a common goal or outcome. Projects were the “containers” to organize activity episodes into the schedules of persons in a household. A heuristic, or rule-based, method was used to organize activities into projects and then to form schedules for interacting household members. Activity generation and scheduling components of TASHA were validated using 1996 and 2001 travel survey data for the Greater Toronto Area (GTA), Canada (Roorda, Miller, & Habib, 2008). The validation proceeded with: (a) verification that TASHA replicated the 1996 base case upon which the model was originally built; and (b) comparison of TASHA's forecast of 2001 daily travel behavior with observed travel survey data for 2001. TASHA activity generation and scheduling model components replicated observed activities with close precision and accuracy for the base year. The distribution of activities in the day was forecasted with relatively high accuracy but TASHA was not able to predict an observed increase in activity participation rate in a five-year forecast. Although the verification and validation results were promising, attention needed to be addressed to reproducing differences in travel behavior in different areas of the Great Toronto Area, in different demographic groups, in different mode choices by time of day, and in different responses to land use and policy scenarios.

FAMOS: The Florida Activity Mobility Simulator (FAMOS) (Pendyala, Kitamura, Kikuchi, Yamamoto, & Fujii, 2005) was a comprehensive multimodal activity-based system for forecasting travel demand. The Household Attributes Generation System (HAGS) and the Prism-Constrained Activity–Travel Simulator (PCATS) were the two main modules composed in FAMOS. HAGS was primarily a population synthesizer and PCATS modeled activity and travel patterns for each person synthesized by HAGS. FAMOS was developed and estimated with 2000 Southeast Florida Household Travel Survey. The basic data requirements for FAMOS included zonal socioeconomic data, zonal network LOS data and household travel survey. FAMOS simulated activity–travel patterns along the continuous time axis while accounting for the interdependency among trips as a result of trip chaining. Since level of service data were used in FAMOS, the forecast output will also have coarse estimation.

CEMDEP: The Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns (CEMDAP) (Bhat, Guo, Srinivasan, & Sivakumar, 2004) used land-use, socio-demographic, activity system, and transportation level-of-service attributes to provide a complete daily activity-travel pattern for each individual in every household of the region. Bhat (Bhat, 2005) (Bhat, 2008) derived a utility theory-based model for discrete/continuous choice that assumed diminishing marginal utility as the level of consumption of any particular alternative increases. The multiple discrete-continuous extreme value (MDCEV) model could capture the discrete–continuous probability of not consuming certain alternatives and consuming given levels of the remaining alternatives better than traditional discrete choice models. However, it only evaluated the time use allocation decisions without considering the time-of-day traffic conditions and considering space and time constraints of the network. Time allocation was the only constraint in the optimization problem in MDCEV.

SimAGENT, the recently developed large scale spatio-temporal simulator of activities and travel for SCAG (Goulias, et al., 2012), was a full-fledged operational activity-based model, that consisted of: PopGen (Ye, Konduri, Pendyala, Sana, & Waddell, 2009), which created the entire resident population of the region, MDCEV, which simulated combinations of joint and solo activities for all persons, CEMDAP, which simulated activity-travel patterns of all individuals in the region for a 24 hour period along a continuous time axis, and other sub models. Thus, the limitation of MDCEV and CEMDAP will be carried over to SimAGENT.

Previous literature related to HAPP

The main concerns regarding the utility maximization-based discrete choice approach are that (Recker, Duan, & Wang, 2008) “(1) the set of feasible solutions (alternatives) in the choice set is infinite, whereas that for standard discrete choice models is countable (and, usually small), (2) the solution vector comprises continuous, as well as discrete variables, (3) although the overall solution represents a mutually exclusive choice, the solution vector itself is composed of components that are not generally mutually exclusive, (4) the components of the utility function are not directly interpretable as utility weights of attributes, but rather are related to these weights through a transformation matrix, and (5) the complexity of the constraint space generally precludes the type of closed-form probability result achievable with standard discrete choice models." A purportedly better approach to address the continuous (time) variables and discrete (a combination of any persons, vehicles, locations, activities) variables, the Household Activity Pattern Problem (HAPP) model, which adopts some well-known network-based formulations in operation research, was proposed by Recker (Recker W. W., 1995). The HAPP model analyzed/predicted the optimal path of household members fulfilling the need of out of home travel knowing *a priori* the agenda. The most general case of HAPP could estimate vehicle transfer, selective activity participation, and ride sharing options. A number of research efforts have followed this ground breaking research since the introduction of HAPP by Recker (Recker W. W., 1995).

The first attempt at application of HAPP was done by Recker and Parimi (Recker & Parimi, 1999). They evaluated the potential environmental impact on efficient trip chaining, ridesharing and fleet technology. The conclusions shed some light on the advantage of using HAPP when traditional trip based modeling could not model complex travel behavior. Recker et al. (Recker, Chen, & McNally, 2001) used HAPP to measure the impact of efficient household travel decisions on potential travel time savings and accessibility gains. Because HAPP could incorporate spatial-temporal constrains and household interaction effects into household travel decisions, it expands the applicability of accessibility considerations to a variety of real-world policy options. Recker (Recker W. W., 2001) demonstrated how HAPP as a mathematical programming formulation could fit into the activity-based demand modeling framework while sustaining utility-maximization principles. Recker et al. (Recker, Duan, & Wang, 2008) introduced a sophisticated estimation procedure to estimate the relative importance of factors associated with HAPP. The method used a genetic algorithm to estimate coefficient values of the utility function, based on a particular multidimensional sequence alignment method to deal with the nominal, discrete attributes of the activity/travel pattern. The estimation procedure was tested on the 1994 Southwest Washington and Oregon Area activity and travel behavior survey. The procedure was very complicated on the top of the complex mathematical programming problem. The complexity of such a methodology prevented further progress in the practical application of HAPP.

Gan and Recker (Gan & Recker, 2008) extended HAPP to be able to capture such activity rescheduling problems as activity cancellation, insertion, and duration adjustment. Chow and Recker (Chow & Recker, 2012) introduced a parameter estimation method to calibrate HAPP so that it could be used for activity-based forecasting. Inverse optimizations for calibrating coefficient of objective function along with goal arrival times were jointly estimated. Although the methodology was innovative and could be used as a reference for application of HAPP, no attention was paid to limitations imposed by the structure of HAPP, which did not incorporate the consideration of difference of activity durations and the difference of travel times and costs by time of day. Kang and Recker (Kang & Recker, 2013) extended HAPP to incorporate location choice (LSP-HAPP) capability and introduced column generation with dynamic programming algorithm to solve LSP-HAPP. However, the application of HAPP was still limited in some simple scenarios due to its focus on the form of the original pickup and delivery problem. Further extension and adjustments are needed to be made for consideration of being an activity-based demand model. Thus, our research will try to close the gap between a practical HAPP and a laboratory HAPP and propose some simple solutions for it.

The body of literature concerning HAPP is already well developed, overcoming barriers against using HAPP as an activity-based forecasting model is still challenging. This research is an effort to incorporate some well-known economic theory into HAPP, such as utility of arrival time preference, utility of activity duration, and by adding time-dependent travel times and travel costs to HAPP by extending the dimension of decision variables.

Chapter 3 THE TIME OF DAY HOUSEHOLD ACTIVITY PATTERN PROBLEM

Introduction

Activity-based modeling approaches are increasingly viewed as a viable alternative to the traditional four-step modeling process, partly, as pointed out by Rasouli and Timmermans (Rasouli & Timmermans, 2013), lack of integration was a serious concern for traditional four-step models. Such integration posed serious difficulties in defining and considering all of the possible combinations of linkages among ’packages’ of decisions affecting travel for the purpose of engaging in activities. But, according to Hägerstrand, (Hägerstraand, 1970) ‘With a suitable technique for grouping constraints in time-space terms, one could perhaps hope to be able to boil down their seemingly tremendous variety into a tractable number.’ HAPP (Household Activity Pattern Problem) has the capability of integrating many decision variables within the space-time constraints described by Hägerstrand. HAPP is a simultaneous decision model, where the solution has considered time and space constraints along with household members, vehicles and time windows. HAPP is adapted from the pickup and delivery problem with time windows (PDPTW), which is a special case of resource constrained shortest path problems. It bears the linearity and also the NP-hard complexity from the original pickup delivery problem. In this chapter, we introduce extensions to the HAPP framework to account for the variation of utility of activity participation both with time-of-day as well as with activity duration. Specifically, we incorporate two important decision considerations into HAPP: 1) the time-of-day activity utility, and 2) the activity duration utility. We propose that there should be three components in the objective function in HAPP: 1) the utility of undertaking an activity i at a particular time of day,

2) the disutility of travel times and costs associated with accessing that activity, and 3) the utility of the duration of participation in the activity. Throughout this research, we will maintain the linearity of HAPP so as not to extend the complexity of the problem, while still keeping it robust enough to address the problem.

Time allocation theory and HAPP

The principal difference between the original HAPP model and that proposed here is that the objective function includes utilities of specific arrival time for participation and utilities of activity duration, together with constraints that reflect arrival time and activity duration preferences. The simplest version of the Household Activity Pattern Problem (HAPP) is one in which the household tries to maximize a cardinal utility function of the form

$$u = U(X, T, S) \tag{3-1}$$

where X denotes the combination of out-of-home activities in which the person participates during the day and their travel linkages, T denotes the vector of arrival times of each activity, S denotes the vector of durations of each activity. Utility u is specified as a function of X, T, S. Without explicitly considering the price of undertaking an activity, this formulation is similar to DeSerpa's (DeSerpa, 1971) work, where a theory of consumer behavior related to time allocation was presented. The household member's utility of travel during the day is related to: in which activity the consumer decides to participate; when the consumer wants to arrive, and how long the consumer wants to spend his/her time in that activity, minus the negative benefit (disutility) of travel required to access the activity. The original formulation of HAPP is concerned only with the latter component, and does not address positive aspects of utility gained from activity performance, but rather treats this aspect as invariant.

The individual is subject to constraints under which choices among all possibilities must be made—this is a constrained optimization problem. We assume that there is a list of mandatory and voluntary activities that belongs to the person to be scheduled for completion. In economic terms, we assume that each activity is a perfect complement to all others—which means that one activity cannot be substituted for by another. Each activity has an independent predetermined ideal utility that may be related to activity types, personal preference, age, gender and other socio-demographic data. We assume that the utility of each activity is independent of each other—undertaking activity A has nothing to do with whether or not the utility of undertaking activity B will change. The feasibility of undertaking both activities A and B may force the person to choose to participate in only one, but choosing either one will not change the utility of the other. Subject to its arrival time, the utility function of the activity is assumed to be dependent only on duration; i.e., the ideal utility of performing that activity will not change during the day, no matter when it starts. Although there are preferences related to arrival times and duration of activities, each household member may face different traffic conditions during the day which may force the change of arrival times and duration of activities.

Accounting for Time-of-day Activity Utility

The utility of arrival time to each activity is related to when the person chooses to arrive at the activity location. Wang (Wang, 1996) estimated that the utility of undertaking an activity varies over the course of the day. Although the estimation shed light on the time preference for activity scheduling, neither time-space constraints nor activity duration decision are incorporated in the analysis, and travel time is estimated in a second-stage decision. Small (Small, 1982) demonstrated a model that can evaluate on-time arrival differences for work trips. However, the arrival time was evaluated independently without considering such other components as time-of-day travel and activity duration. For example, Small's model could evaluate the sensitivity of on-time arrival for work activities, but the model could not estimate what would happen if the consumer arrived early (late). Would the consumer decide to stay at work for a little longer (shorter) or would all of the remaining activities be scheduled earlier (later)? To address these shortcomings, a model that can simultaneously consider arrival time, activity duration, activity assignment, activity chaining and mode choice is required. As pointed out by Ashiru et al. (Ashiru, Polak, & Noland., 2004), 'The choices of timing and duration of activities are closely interrelated; however, few researchers have attempted to study this relationship. Instead strong separability assumptions have been made concerning the timing and duration dimensions.' We will show that HAPP can be extended to incorporate all of these components and generate an optimal solution.

The original time window constraints in HAPP treat the activity arrival utility function as a uniform distribution function that has no preference for arrival time as long as it is within the pre-specified time window constraints. Here, we assume that activity arrival utility functions are given and identically perceived by the same behaviorally homogeneous group. Activity arrival utility functions are time dependent. Assume that the utility of undertaking the activity i at the time of day for person α is a function of the arrival time $\mathrm{T}_{\mathrm{i}}^{\alpha}$, i.e., is $f(\mathrm{T}_{\mathrm{i}}^{\alpha})$. For simplicity, we hypothesize that the utility function $f(\mathrm{T}_{\mathrm{i}}^{\alpha})$ can be represented by a triangular distribution with mode arrival time μ_i^{α}, earliest arrival time a_i^{α}, latest arrival time b_i^{α} , and shape parameters $\mathrm{K}_{\mathrm{ie}}^{\alpha}$

and K_{il}^{α} (Figure 3.1). We do not set up a hard time window constraint on arrival time, but if the person arrives earlier than a_i^{α}, or later than b_i^{α}, it will have zero utility. The utility function $f(T_i^{\alpha})$ of arrival time on any activity is

$$f(T_i^{\alpha}) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ 0 \le T_i^{\alpha} < a_i^{\alpha} \tag{3-2a}$$

$$f(T_i^{\alpha}) = K_{ie}^{\alpha}(T_i^{\alpha} - a_i^{\alpha}), \qquad i \in L, \alpha \in \eta, \qquad if\ a_i^{\alpha} \le T_i^{\alpha} \le \mu_i^{\alpha} \tag{3-2b}$$

$$f(T_i^{\alpha}) = K_{il}^{\alpha}(T_i^{\alpha} - b_i^{\alpha}), \qquad i \in L, \alpha \in \eta, \qquad if\ \mu_i^{\alpha} < T_i^{\alpha} \le b_i^{\alpha} \tag{3-2c}$$

$$f(T_i^{\alpha}) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ b_i^{\alpha} < T_i^{\alpha} \tag{3-2d}$$

Although other probability distributions (such as using a bell-shaped temporal utility profiles as the time of day activity utility (Ashiru, Polak, & Noland., 2004)) can be chosen, we choose a triangular distribution to maintain the linearity of HAPP.

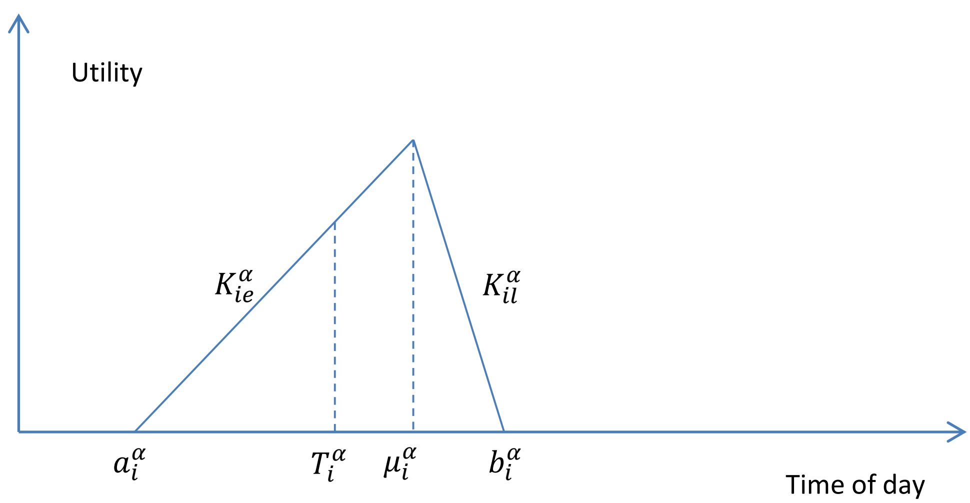

Figure 3.1 The utility of activity i starts at T_i^{α} of person α

Accounting for Duration Effects in Activity Participation

Utility is not associated just with arrival time; the activity gain of each activity is highly related to its duration. In most current activity-based models, activity arrival time and activity duration are estimated in separate models. The hazard duration function is the most pervasive model to evaluate activity duration. Bhat (Bhat, 1996) examined the factors affecting shopping activity duration during the return home trip from work and developed a comprehensive methodological framework to estimate a stochastic hazard-based duration model from grouped (interval-level) failure data. However, as pointed out by Ettema et al. (Ettema, Bastin, Polak, & Ashiru, 2007), 'A drawback of hazard modelling, however, is that it provides only a statistical approach to modelling distributions of durations, which lacks an underlying behavioral theory.' With the hazard duration model it is not easy to set up linkages among different activities and household members and their relation to traffic conditions. More specifically, each activity is evaluated in isolation without considering the activity chaining and the activity arrival time choices. Although the relationship between activity durations and the complex decision process of ending an activity at any time can be represented using a time allocation model, to our knowledge only HAPP can incorporate a time allocation model in a way that brings components together within a travel constraint space to generate a simultaneous solution.

In economics, Becker (Becker, 1965) presented a theory of the allocation of time between different activities. The theory assumed that households were producers and consumers, where they produced commodities by combining inputs of goods and time according to the cost-minimization rule of the traditional theory of the firm. Commodities (activities) were produced in quantities determined by maximizing a utility function of the commodity set subject to prices and a constraint on resources. Resources were measured by what was called full income, which was the sum of money income and that forgone or 'lost' by the use of time and goods to obtain utility, while commodity prices were measured by the sum of the costs of their goods and time inputs. DeSerpa (DeSerpa, 1971) developed a model to handle economic problems wherein a time dimension was relevant. The essential features of the model include: '1) utility is a function of commodities and also the allocation of time; 2) a money constraint and a time constraint are two resource constraints of consumer decisions; 3) any commodity requires an allocation of a minimum amount of time, but consumers can spend more time on that activity if he/she desires.' Although Becker was the first to propose to attach a value to the time that was allocated to an activity and Deserpa established the theoretical relationship between those three features in time allocation theory, according to Mackie et al. (PJ Mackie, 2001), two dimensions of a value attached to travel savings were missing: 'the variation in goods consumption due to the substitution of travel for other activities,' and 'the possibility of re-timing activities in order to undertake them according to a preferred schedule'. With that being said, we try to combine Deserpa's time allocation model with Small's work on trip departure estimation as well as Wang's arrival time utility estimation, into HAPP.

In the original HAPP model, the activity duration (s_i^α) is a fixed, given constant, which cannot reflect changes of other components of the decision process relative to changes in activity duration. To incorporate flexible activity duration and the heterogeneity of personal characteristics into HAPP, we introduce a new decision variable

$$S_i^\alpha \geq s_{i\_min}^\alpha, i \in L, \alpha \in \eta$$

where S_i^α is the actual activity duration, $s_{i\_min}^\alpha$ is the minimum activity duration, both of which vary depending on the specific person α and activity i, and L and η are the lists of activities in the agenda and the set of persons in the household, respectively. Here, we introduce a piecewise linear activity duration function (Figure 3.2). For an activity $i,$ there is a minimum time $s_{i\_min}^{\alpha}$ to undertake the activity for person α and the person may get more utility if he/she spends more time on it. The simplest case is assuming that the utility gain from each unit of time spent is linear, up to a maximum (or ideal) duration, with a requirement of minimum duration. Depending on the characteristic of the activity, different shapes of the linear duration function can be introduced. The slope of K_{is}^{α} determines how flexible the duration of activity is. As pointed out by Jara-Diaz (Jara-Díaz, 2003), 'one cannot work continuously', there will be an upper bound on the maximum utility gain. Thus, the slope of utility gain on activity duration will be flat after the maximum utility gain. Also, the person may not be able to spend more time on any particular activity because he/she may have commitments on other activities or may lose the opportunity to undertake other activities. This may relate to the concept of satiation effect or opportunity cost in economics—the gain in spending more time on one activity may not be as valuable as spending the time on an additional activity that requires a minimum amount of time $s_{j\_min}^{\alpha}$. Of course, depending on the activity and the person, the minimum utility of undertaking that activity can also be different. As shown in Figure 3.2, the utility characteristics can be determined by the minimum utility $U_{i\_min}^{\alpha}$, maximum utility $U_{i\_max}^{\alpha}$, the slope K_{is}^{α}, the minimum spending time $s_{i\_min}^{\alpha}$ and the maximum spending time $s_{i\_max}^{\alpha}$. This form is very close to the S-Shaped activity utility function proposed by Joh et al. (Joh, Arentze, & Timmermans, 2004) and Bladel (Bladel, Bellemans, Wets, Arentze, & Timmermans, 2006). The assumed utility function $g(S_i^{\alpha})$ of activity duration for any activity can thus be represented as:

$$g(S_i^{\alpha}) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^{\alpha} = 0, \tag{3-3a}$$

$$g(S_i^{\alpha}) = U_{i\_min}^{\alpha}, \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^{\alpha} < s_{i\_min}^{\alpha}, \tag{3-3b}$$

$$g(S_i^\alpha) = U_{i\_min}^\alpha + K_{is}^\alpha\left(S_i^\alpha - s_{i\_min}^\alpha\right), \qquad i \in L, \alpha \in \eta, \qquad if\ s_{i\_min}^\alpha \leq S_i^\alpha < s_{i\_max}^\alpha, \tag{3-3c}$$

$$g(S_i^\alpha) = U_{i\_min}^s + K_{is}^\alpha\left(s_{i\_max}^\alpha - s_{i\_min}^\alpha\right), \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^\alpha \geq s_{i\_max}^\alpha, \tag{3-3d}$$

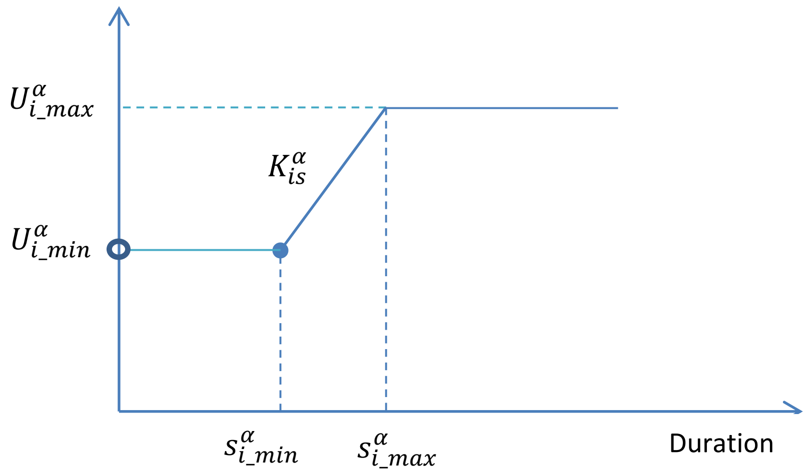

Figure 3.2 Utility on duration of activity i of person α

Model formulation

The formulation of HAPP with consideration of time-of-day activity utility and duration utility (UHAPPP) is

$$Maximize\ U(\boldsymbol{X}_i) = \boldsymbol{\beta}_i' \cdot \boldsymbol{X}_i \tag{3-4}$$

$$\text{subject to } \boldsymbol{B}\boldsymbol{X}_i \leq 0, \tag{3-5}$$

where

$\boldsymbol{X}_i = [\boldsymbol{X}^v \quad \boldsymbol{H}^\alpha \quad \boldsymbol{T}^\alpha \quad \boldsymbol{S}^\alpha]'$, $\boldsymbol{X}^v = \left[X_{\boldsymbol{ij}}^v = \begin{Bmatrix} 0 \\ 1 \end{Bmatrix}\right]$, $\boldsymbol{H}^\alpha = \left[H_{\boldsymbol{ij}}^\alpha = \begin{Bmatrix} 0 \\ 1 \end{Bmatrix}\right]$, $\boldsymbol{T}^\alpha = [T_i^\alpha \geq 0]$, $\boldsymbol{S}^\alpha =$ $[S_i^\alpha \geq 0]$, $\boldsymbol{\beta_i} = [\beta_i^\alpha]$, X^v is the decision variable on vehicle flow; H^α is the decision variable on person flow; T^α is the decision variable on arrival time; S^α is the decision variable on activity duration; β_i^α is the weight of objective imposed by each person and each activity. Equation (3-4) and (3-5) define UHAPP in matrix format. A detail version of UHAPP is defined as follow.

$A = \{1, 2, \dots, i, \dots, n\}$	Set of out-of-home activities scheduled to be completed by travelers in the household.
$\eta = \{1, 2, \dots, \|\eta\|\}$	Set of household members with driver license.
$V = \{1, 2, \dots, v, \dots, \|V\|\}$	Set of vehicles used by travelers in the household to complete their scheduled activities.
$L^+ = \{1, 2, \dots, i, \dots, n\}$	Set of designating location at which each activity is performed.
$L^- = \{n+1, n+2, \dots, n+i, \dots, 2n\}$	Set of designation the ultimate destination of the return-to-home trip for each activity. (It is noted that the physical location of each element of L^- is home.)
$\Omega_H^\alpha \subset A$	The subset of activities that cannot be performed by person α
$[a_i, b_i]$	The hard time window of activity i can be performed
S_i^α	The amount of time spent on activity i by household member α.
t_{ij}^v	The travel time from the location of activity i to the location of activity j using vehicle v.
c_{ij}^v	The travel cost from the location of activity i to the location of activity j using vehicle v.
$L = L^+ \cup L^-$	Set of nodes comprising completion of the household's

	scheduled activities.
$O = \{0, L^{-}, 2n + 1\}$	Set of home nodes
$D = \{L^{+}, L^{-}, 2n + 1\}$	Set of destination nodes
$N = \{0, L, 2n + 1\}$	The set of all nodes, including those associated with the initial departure and final return to home.
$X_{ij}^{v}, i, j \in N, v \in V, i \neq j$	Binary decision variable equal to unity if vehicle v travels from activity i to activity j, and zero otherwise.
$H_{ij}^{\alpha}, i, j \in N, \alpha \in \eta, i \neq j$	Binary decision variable equal to unity if household member α travels from activity i to activity j, and zero otherwise.
$T_{i}^{\alpha}, i \in L, \alpha \in \eta$	The time at which household member α participation in activity i begins.
$K_{v}, v \in V$	The initial cost of using vehicle v of performing out-of-home activities
β_{i}^{α}	The weight of objective imposed by each person and each activity.
M	A large positive number

With these definitions, the objective function of UHAPP can be represented as

$$Max\ U = \sum_{i\in D}\sum_{\alpha\in\eta}\beta_{1i}^{\alpha} f(T_i^{\alpha})\sum_{j\in N} H_{ij}^{\alpha} - \sum_{v\in V}\sum_{i\in N}\sum_{j\in N} t_{ij}^{v} X_{ij}^{v}\sum_{\alpha\in\eta}\beta_2^{\alpha} H_{ij}^{\alpha} - \beta_3\sum_{v\in V}\sum_{i\in O}\sum_{j\in L^+} K_v X_{ij}^{v} - \sum_{v\in V}\sum_{i\in N}\sum_{j\in N} c_{ij}^{v} X_{ij}^{v}\sum_{\alpha\in\eta}\beta_4^{\alpha} H_{ij}^{\alpha} + \sum_{i\in L^+}\sum_{\alpha\in\eta}\beta_{5i}^{\alpha} g(S_i^{\alpha})\sum_{j\in N} H_{ij}^{\alpha} \tag{3-6a}$$

Under the assumption that the utility functions for arrival time and duration do not vary over individuals within the household, Equation (3-6a) becomes

$$Max\ U = \sum_{\alpha\in\eta}\sum_{i\in D}\sum_{j\in N}\beta_{1i} f(T_i^{\alpha}) H_{ij}^{\alpha} - \beta_2\sum_{v\in V}\sum_{i\in N}\sum_{j\in N} t_{ij}^{v} X_{ij}^{v} - \beta_3\sum_{v\in V}\sum_{i\in O}\sum_{j\in L^+} K_v X_{ij}^{v} - \beta_4\sum_{v\in V}\sum_{i\in N}\sum_{j\in N} c_{ij}^{v} X_{ij}^{v} + \sum_{\alpha\in\eta}\sum_{i\in L^+}\sum_{j\in N}\beta_{5i} g(S_i^{\alpha}) H_{ij}^{\alpha} \tag{3-6b}$$

where $\sum_{\alpha\in\eta}\sum_{i\in D}\sum_{j\in N}\beta_{1i} f(T_i^{\alpha}) H_{ij}^{\alpha}$ is the total utility of arrival time for the household, $\beta_2\sum_{v\in V}\sum_{i\in N}\sum_{j\in N} t_{ij}^{v} X_{ij}^{v}$ is the total disutility of time spent traveling during the day, $\beta_3\sum_{v\in V}\sum_{i\in O}\sum_{j\in L^+} K_v X_{ij}^{v}$ is the total initial cost of using a vehicle for out of home activities, (of course, we can include the parking cost for the other end of travel, but for simplicity reasons, we do not include the parking cost in the objective function; however, we note that UHAPP is capable on evaluating travel decisions related to parking cost policies). $\beta_4\sum_{v\in V}\sum_{i\in N}\sum_{j\in N} c_{ij}^{v} X_{ij}^{v}$ is the total disutility of travel cost during the day; this includes any tolls, fuel consumption and other monetary costs. $\sum_{\alpha\in\eta}\sum_{i\in L^+}\sum_{j\in N}\beta_{5i} g(S_i^{\alpha}) H_{ij}^{\alpha}$ is the total utility of time spent participating in the activity. The sum of these objective components is subject to the following constraints:

$$\sum_{v\in V}\sum_{j\in N} X_{ij}^{v} = 1, \qquad i\in L^+ \tag{3-7}$$

$$\sum_{j\in N} X_{ij}^{v} - \sum_{j\in N} X_{ji}^{v} = 0, \qquad i \in L, v \in V \tag{3-8}$$

$$\sum_{j\in L^{+}} X_{0j}^{v} \leq 1, \qquad v \in V \tag{3-9}$$

$$\sum_{j\in L^{-}} X_{j,2n+1}^{v} \leq 1, \qquad v \in V \tag{3-10}$$

$$\sum_{j\in N} X_{ji}^{v} - \sum_{j\in N} X_{j,n+i}^{v} = 0, \qquad i \in L^{+}, v \in V \tag{3-11}$$

$$X_{ij}^{v} = \begin{cases} 0 \\ 1 \end{cases}; \quad i, j \in N, v \in V \tag{3-12}$$

$$\sum_{j\in L^{-}} X_{0,j}^{v} = 0, \qquad v \in V \tag{3-13}$$

$$\sum_{i\in N} X_{i,0}^{v} = 0, \qquad v \in V \tag{3-14}$$

$$\sum_{i\in L^{+}} X_{i,2n+1}^{v} = 0, \qquad v \in V \tag{3-15}$$

$$\sum_{j\in N} X_{2n+1,j}^{v} = 0, \qquad v \in V \tag{3-16}$$

$$\sum_{i\in L^{+}} X_{i+n,i}^{v} = 0, \qquad v \in V \tag{3-17}$$

$$\sum_{j\in N} X_{j,j}^{v} = 0, \qquad v \in V \tag{3-18}$$

$$X_{i,j}^{v} + X_{j,i}^{v} \leq 1, \qquad i, j \in L^{-}, v \in V \tag{3-19}$$

$$\sum_{\alpha\in\eta} \sum_{j\in N} H_{ij}^{\alpha} = 1, \qquad i \in L^{+} \tag{3-20}$$

$$\sum_{j\in N} H_{ij}^{\alpha} - \sum_{j\in N} H_{ji}^{\alpha} = 0, \qquad i \in L, \alpha \in \eta \tag{3-21}$$

$$\sum_{j \in L^+} H_{0j}^{\alpha} \leq 1, \qquad \alpha \in \eta \tag{3-22}$$

$$\sum_{j \in L^-} H_{i,2n+1}^{\alpha} \leq 1, \qquad \alpha \in \eta \tag{3-23}$$

$$\sum_{j \in N} H_{ji}^{\alpha} - \sum_{j \in N} H_{j,n+i}^{\alpha} = 0, \qquad i \in L^+, \alpha \in \eta \tag{3-24}$$

$$a_i - T_i^{\alpha} \leq \left(2 - \sum_{j \in L} H_{ij}^{\alpha} - \sum_{j \in L} X_{ij}^{v} \right) M, \qquad i \in L^+, \alpha \in \eta, v \in V \tag{3-25a}$$

$$T_i^{\alpha} - b_i \leq \left(2 - \sum_{j \in L} H_{ij}^{\alpha} - \sum_{j \in L} X_{ij}^{v} \right) M, \qquad i \in L^+, \alpha \in \eta, v \in V \tag{3-25b}$$

$$T_i^{\alpha} + S_i^{\alpha} + t_{i,n+i}^{v} - T_{n+i}^{\alpha} \leq \left(2 - \sum_{k \in N} X_{k,i}^{v} - \sum_{j \in N} H_{j,i}^{\alpha} \right) M, \qquad i \in L^+, \alpha \in \eta, v \in V \tag{3-26}$$

$$T_i^{\alpha} + S_i^{\alpha} + t_{ij}^{v} - T_j^{\alpha} \leq \left(2 - H_{ij}^{\alpha} - X_{ij}^{v} \right) M, \qquad i,j \in L, \alpha \in \eta, v \in V \tag{3-27a}$$

$$T_i^{\alpha} + S_i^{\alpha} + t_{ij}^{v} - T_j^{\alpha} \geq -\left(2 - H_{ij}^{\alpha} - X_{ij}^{v} \right) M, \qquad i,j \in L, \alpha \in \eta, v \in V \tag{3-27b}$$

$$T_j^{\alpha} \leq \sum_{i \in N} H_{ij}^{\alpha} M, \qquad j \in L, \alpha \in \eta \tag{3-28}$$

$$S_j^{\alpha} \leq \sum_{i \in N} H_{ij}^{\alpha} M, \qquad j \in L, \alpha \in \eta \tag{3-29a}$$

$$S_i^{\alpha} \leq (1 - \sum_{j \in L^-} H_{ij}^{\alpha})\, M, \qquad i \in L^-, \alpha \in \eta \tag{3-29b}$$

$$S_j^{\alpha} - s_{j\_min}^{\alpha} \geq (\sum_{i \in N} H_{ij}^{\alpha} - 1) M, \qquad j \in L^+, \alpha \in \eta \tag{3-30}$$

$$T_0^{\alpha} + t_{0j}^{v} - T_j^{\alpha} \leq \left(2 - H_{0j}^{\alpha} - X_{0j}^{v} \right) M, \qquad j \in L^+, \alpha \in \eta, v \in V \tag{3-31a}$$

$$T_0^{\alpha} + t_{0j}^{v} - T_j^{\alpha} \geq -\left(2 - H_{0j}^{\alpha} - X_{0j}^{v} \right) M, \qquad j \in L^+, \alpha \in \eta, v \in V \tag{3-31b}$$

$$T_i^\alpha - T_{2n+1}^\alpha \leq \left(2 - H_{i,2n+1}^\alpha - X_{i,2n+1}^v\right)M, \qquad i \in L^-, \alpha \in \eta, v \in V \tag{3-32}$$

$$f(T_i^\alpha) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ 0\ \leq T_i^\alpha < a_i^\alpha \tag{3-33a}$$

$$f(T_i^\alpha) = K_{ie}^\alpha(T_i^\alpha - a_i^\alpha), \qquad i \in L, \alpha \in \eta, \qquad if\ a_i^\alpha\ \leq T_i^\alpha \leq \mu_i^\alpha \tag{3-33b}$$

$$f(T_i^\alpha) = K_{il}^\alpha(T_i^\alpha - b_i^\alpha), \qquad i \in L, \alpha \in \eta, \qquad if\ \mu_i^\alpha < T_i^\alpha \leq b_i^\alpha \tag{3-33c}$$

$$f(T_i^\alpha) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ b_i^\alpha < T_i^\alpha \tag{3-33d}$$

$$f(T_{2n+1}^\alpha) = 0, \qquad \alpha \in \eta, \qquad if\ 0\ \leq T_{2n+1}^\alpha < a_{2n+1}^\alpha \tag{3-34a}$$

$$f(T_{2n+1}^\alpha) = K_{2n+1,e}^\alpha(T_{2n+1}^\alpha - a_{2n+1}^\alpha), \qquad \alpha \in \eta, \qquad if\ a_{2n+1}^\alpha \leq T_{2n+1}^\alpha \leq \mu_{2n+1}^\alpha, \tag{3-34b}$$

$$f(T_{2n+1}^\alpha) = K_{2n+1,l}^\alpha(T_{2n+1}^\alpha - b_{2n+1}^\alpha), \qquad \alpha \in \eta, \qquad if\ \mu_{2n+1}^\alpha < T_{2n+1}^\alpha \leq b_{2n+1}^\alpha, \tag{3-34c}$$

$$f(T_{2n+1}^\alpha) = 0, \qquad \alpha \in \eta, \qquad if\ b_{2n+1}^\alpha < T_{2n+1}^\alpha, \tag{3-34d}$$

$$g(S_i^\alpha) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^\alpha = 0, \tag{3-35a}$$

$$g(S_i^\alpha) = U_{i\_min}^\alpha, \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^\alpha < s_{i\_min}^\alpha, \tag{3-35b}$$

$$g(S_i^\alpha) = U_{i\_min}^\alpha + K_{is}^\alpha\left(S_i^\alpha - s_{i\_min}^\alpha\right), \qquad i \in L, \alpha \in \eta, \qquad if\ s_{i\_min}^\alpha \leq S_i^\alpha < s_{i\_max}^\alpha, \tag{3-35c}$$

$$g(S_i^\alpha) = U_{i\_min}^s + K_{is}^\alpha\left(s_{i\_max}^\alpha - s_{i\_min}^\alpha\right), \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^\alpha \geq s_{i\_max}^\alpha, \tag{3-35d}$$

$$\sum_{j \in P^-} H_{0,j}^\alpha = 0, \qquad \alpha \in \eta \tag{3-36}$$

$$\sum_{i \in N} H_{i,0}^\alpha = 0, \qquad \alpha \in \eta \tag{3-37}$$

$$\sum_{i \in L^+} H_{i,2n+1}^\alpha = 0, \qquad \alpha \in \eta \tag{3-38}$$

$$\sum_{j \in N} H_{2n+1,j}^\alpha = 0, \qquad \alpha \in \eta \tag{3-39}$$

$$\sum_{i \in L^+} H_{i+n,i}^\alpha = 0, \qquad \alpha \in \eta \tag{3-40}$$

$$\sum_{j \in N} H_{j,j}^\alpha = 0, \qquad \alpha \in \eta \tag{3-41}$$

$$H_{i,j}^{v} + H_{j,i}^{v} \leq 1, \qquad i,j \in L^{-}, v \in V \tag{3-42}$$

$$\sum_{j \in \Omega_H^{\alpha}} \sum_{i \in L} H_{ij}^{\alpha} = 0, \qquad \alpha \in \eta \tag{3-43}$$

$$H_{ij}^{\alpha} = \begin{cases} 0 \\ 1 \end{cases}; \quad i,j \in N, \alpha \in \eta \tag{3-44}$$

$$\sum_{\alpha \in \eta} H_{ij}^{\alpha} = \sum_{v \in V} X_{ij}^{v}, \qquad i \in L, j \in L \tag{3-45}$$

$$\sum_{\alpha \in \eta} H_{0j}^{\alpha} = \sum_{v \in V} X_{0j}^{v}, \qquad j \in L^{+} \tag{3-46}$$

$$\sum_{\alpha \in \eta} H_{i,2n+1}^{\alpha} = \sum_{v \in V} X_{i,2n+1}^{v}, \qquad i \in L^{-} \tag{3-47}$$

Relationships (3-6)-(3-47) define the Utility-based Household Activity Pattern Problem (UHAPP). Constraints (3-7) and (3-20) guarantee that every activity will be performed and at most visited by one vehicle and one person. Constraints (3-8) and (3-21) ensure that every vehicle and every person that go into the node have to leave the same node. Constraints (3-9), (3-10), (3-22), (3-23) mean not every vehicle and every person have to connect to one activity location; they can stay at home if desired. Constraints (3-11) and (3-24) warrant that every activity location is associated with one drop off location which is home connected by vehicle flow and person flow. Constraints (3-12) and (3-44) ensure the integer solution on vehicle flow and person flow. Constraints (3-13)-(3-19) and (3-36)-(3-42) sort out of those unreasonable vehicle flows and person flows to make sure the solution makes sense. Constraints (3-25) are time window constraints which represent operation (business) hours for offices, restaurants, stores, where hard time windows are set up. Constraints (3-26) ensure every drop off activity happens later than the pickup activity. Constraints (3-27) define the arrival time relationship for two consecutive nodes. Constraints (3-28)-(3-29) assign activity arrival time and activity duration to persons staying at home. Constraints (3-30) guarantee the minimum activity duration. Constraints (3-31)-(3-32) assign leave home time at the beginning of the day and arrival time at the end of day to each person. Because there is no duration for at home activities and no travel time between the last drop of node and home, constraints (3-31)-(3-32) are separated from constraints (3-27). Constraints (3-33)-(3-34) define the utility function of arrival time. To convert the 'if statements' to integer linear programming format, we need to add more integer variables. We define

$$I_1, I_2, I_3 = \begin{cases} 0 \\ 1 \end{cases};$$

Constraints (3-33) can be transformed to constraints (3-48)

$$a_i^\alpha - T_i^\alpha \leq (1 - I_1)M \tag{3-48a}$$

$$T_i^\alpha - \mu_i^\alpha \leq (1 - I_2)M \tag{3-48b}$$

$$T_i^\alpha - b_i^\alpha \leq (1 - I_3)M \tag{3-48c}$$

$$f(T_i^\alpha) = [K_{ie}^\alpha (T_i^\alpha - a_i^\alpha) I_2 + K_{il}^\alpha (T_i^\alpha - b_i^\alpha)(1 - I_2)] \cdot I_1 \cdot I_3, \qquad i \in L, \alpha \in \eta \tag{3-48d}$$

The same treatment can be applied to constraints (3-34). Constraints (3-35) define the utility function of activity duration. We also transform the 'if statements' in constraints (3-35) to integer linear programming constraints the same way as constraints (3-48). By transforming the arrival time utility function and utility function of duration to linear expressions and by reformulating these constraints as integer linear programming constraints, we escape the assumption of nonlinear functions that would significantly increase the complexity of the solution algorithm. Unlike the original HAPP model, where most of the constraints are related to vehicle flows, we focus more on persons and put scheduling constraints on persons as the core of the activity-based model. For more details on the role of each constraint, readers can refer to the original HAPP case 4 in Recker's (Recker W. W., 1995) paper.

Hypothetical examples

To demonstrate how solutions to UHAPP can differ from those obtained using the original HAPP, we first apply the UHAPP model to some hypothetical case scenarios. We generate a sample dataset that includes a two-person household with two vehicles available for use during the day. Three activities with their utility functions for arrival time and duration specified are to be undertaken by the end of the day. Each person has a mandatory activity to perform. One voluntary activity needs to be assigned to one person. We assume one mode (auto) is available for this household from which to choose. Table 3.1 contains the basic demographic data of the household and activities. Ω_H^α has the same meaning as the original HAPP; $\Omega_H^1 = \{2\}$ means activity 2 cannot be performed by person 1. Table 3.2 specifies the earliest arrival time (the intersection of 0 utility in the utility function on the left of mode arrival time), peak arrival time (mode arrival time), the latest arrival time (the intersection of 0 utility in the utility function on the right of mode arrival time), the coefficient for each linear utility function. Table 3.3 contains the minimum activity duration utility, minimum activity duration, maximum activity duration and the coefficient for each linear utility function. Table 3.4 and Table 3.5 are travel times and travel cost for each pair of nodes, respectively. We divide the 24-hour day into 1440 minutes to simplify the analysis. We will assume $\beta_{1\mathrm{i}} = \beta_2 = \beta_3 = \beta_4 = \beta_{5\mathrm{i}} = 1$, and set $\mathrm{M} = 1500$ in all the following numerical examples. We first run this input data using the original HAPP model. We set this data set as the base case scenario to run UHAPP. Then we change some parameters on arrival utility function as case 1 scenario. We change the coefficient of the duration utility function as case 2 scenario, and change the relative weight $\beta_{\alpha i}$ in the objective function as case 3 scenario. We want to compare different solutions by different models (HAPP and UHAPP) and different utility function on arrival and duration as well as the relative weight $\beta_{\alpha i}$ in the objective function in order to further understand how each component will change the solution respectively.

Table 3.1 Hypothetical data set

Known variables	Variable set
Household members	$\eta = \{1,2\}$
Available vehicles	$V = \{1,2\}$
Out-of-home activities	$A = \{1,2,3\}$
Activity compatibility	$\Omega_H^1 = \{2\}, \Omega_H^2 = \{1\}$
Activity hard time windows	$[a_i, b_i] = \begin{bmatrix} 6:00 & 24:00 \\ 6:00 & 24:00 \\ 10:00 & 21:00 \end{bmatrix}$
Initial cost of vehicles	$K_1 = K_2 = 10$

Table 3.2 Linear utility function of each person on each destination a_i^α, μ_i^α, b_i^α, K_{ie}^α and K_{il}^α

Destination (i)	a_i^1	a_i^2	μ_i^1	μ_i^2	b_i^1	b_i^2	K_{ie}^1	K_{ie}^2	K_{il}^1	K_{il}^2
1	5:30	0	8:20	0	15:00	0	0.16	0	-0.068	0
2	0	6:00	0	9:00	0	15:00	0	0.18	0	-0.09
3	9:00	8:30	15:30	16:00	18:00	18:30	0.04	0.05	-0.104	-0.15
4	15:00	0	16:00	0	18:40	0	0.08	0	-0.03	0
5	0	15:00	0	16:00	0	18:40	0	0.09	0	-0.03375
6	10:30	11:00	17:00	17:30	21:00	21:30	0.02	0.025	-0.0325	-0.040625
7	15:00	15:00	17:30	18:00	21:40	22:00	0.1	0.1	-0.06	-0.075

Table 3.3 Utility function of duration $U^{\alpha}_{i\_min}$, $s^{\alpha}_{i\_min}$, $s^{\alpha}_{i\_max}$ and K^{α}_{is}

Activity (i)	$U^1_{i\_min}$	$U^2_{i\_min}$	$s^1_{i\_min}$	$s^2_{i\_min}$	$s^1_{i\_max}$	$s^2_{i\_max}$	K^1_{is}	K^2_{is}
1	7	0	300	0	540	0	0.1	0
2	0	7	0	360	0	570	0	0.12
3	3	3	15	20	90	120	0.08	0.06

Table 3.4 Travel times for each node to node pair (minutes)

NODES	0	1	2	3	4	5	6	7
0	0	30	35	40	0	0	0	0
1	30	0	20	15	30	30	30	30
2	35	20	0	25	35	35	35	35
3	40	15	25	0	40	40	40	40
4	0	30	35	40	0	0	0	0
5	0	30	35	40	0	0	0	0
6	0	30	35	40	0	0	0	0
7	0	30	35	40	0	0	0	0

Table 3.5 Travel costs for each node to node pair (dollar)

NODES	0	1	2	3	4	5	6	7
0	0	3	3.5	4	0	0	0	0
1	3	0	2	1.5	3	3	3	3
2	3.5	2	0	2.5	3.5	3.5	3.5	3.5
3	4	1.5	2.5	0	4	4	4	4
4	0	3	3.5	4	0	0	0	0
5	0	3	3.5	4	0	0	0	0
6	0	3	3.5	4	0	0	0	0
7	0	3	3.5	4	0	0	0	0

We first run the original HAPP with activity duration $s^1_1 = 300$, $s^2_2 = 360$, $s^1_3 = s^2_3 = 15$ in AMPL, which is a modeling language for linear and nonlinear optimization problems. We call CPLEX 12.5.1 in AMPL and, after 58 MIP and 0 branch-and-bound nodes, we have an optimal solution of U=-190.5. (It is negative because the objective function in original HAPP is to minimize the disutility in travel times and travel costs, which has been transformed to maximize the negative disutility in UHAPP.) The solutions of vehicle flows and person flows are posted in Table 3.6. The solutions of arrival time and activity duration are posted in Table 3.7. The solution shows that person 1 leaves home at 9:20, arrives to activity 3 at 10:00, spends 15 minutes at activity 3, arrives at activity 1 at 10:30 and spends 300 minutes in activity 1. Person 2 leaves home at 5:25, arrives at activity 2 at 6:00, and spends 360 minutes in activity 2. Because there is no utility on the arrival time and no utility on activity duration, person 1 and person 2 both arrive at their activities as early as the activity operation time windows become available (10:00 and 6:00), and the activity duration is known (300, 360 and 15) as an input before we run HAPP. Thus, without considering utilities of activity arrival and utilities of activity duration, the original HAPP cannot estimate (has no preference for) arrival time and activity duration, as well as their interactions.

Table 3.6 Vehicle flows and person flows from HAPP

Nodes (N)	Nodes (N)	Vehicles(V)	Persons (η)	X_{ij}^{1}	X_{ij}^{2}	H_{ij}^{1}	H_{ij}^{2}
0	2	2	2	0	1	0	1
0	3	1	1	1	0	1	0
1	4	1	1	1	0	1	0
2	5	2	2	0	1	0	1
3	1	1	1	1	0	1	0
4	6	1	1	1	0	1	0
5	7	2	2	0	1	0	1
6	7	1	1	1	0	1	0

Table 3.7 Arrival time and activity duration rom HAPP

Nodes (N)	Persons (η)	T_i^α	S_i^α
0	1	9:20	-
0	2	5:25	-
1	1	10:30	300
2	2	6:00	360
3	1	10:00	15
4	1	16:00	0
5	2	12:35	0
6	1	16:00	0
7	1	16:00	-
7	2	12:35	-

Now, let's run the UHAPP model with assumed known utility functions for activity arrival and activity duration, specified in Table 3.2 and Table 3.3, in AMPL. We set these input as the base case scenario. We call CPLEX 12.5.1 in AMPL and after 6763 MIP simplex iterations and 1614 branch-and-bound nodes, we have an optimal solution of U=-19.35. We note that the objective is negative because the weight of travel times and travel costs in this artificial scenario are dominant in the objective function. The solutions of vehicle flows and person flows are posted in Table 3.8. The solutions of arrival time and activity duration are posted in Table 3.9 with the reduce cost in the optimal solution.

Table 3.8 Vehicle flows and person flows from UHAPP at base case scenario

Nodes (N)	Nodes (N)	Vehicles(V)	Persons (η)	X_{ij}^1	X_{ij}^2	H_{ij}^1	H_{ij}^2
0	1	1	1	1	0	1	0
0	2	2	2	0	1	0	1
1	3	1	1	1	0	1	0
2	5	2	2	0	1	0	1

3	4	1	1	1	0	1	0
4	6	1	1	1	0	1	0
5	7	2	2	0	1	0	1
6	7	1	1	1	0	1	0

Table 3.9 Arrival time and activity duration from UHAPP at base case scenario

Nodes ($\mathbf{N}$)	Persons ($\boldsymbol{\eta}$)	$\mathbf{T_i^{\alpha}}$	$\mathbf{T_i^{\alpha}.RC}$	$\mathbf{S_i^{\alpha}}$	$\mathbf{S_i^{\alpha}.RC}$
0	1	7:50	0	-	-
0	2	8:25	0	-	-
1	1	8:20	0	415	0
2	2	9:00	0	570	0
3	1	15:30	0.02	80	0
4	1	17:30	0	0	0
5	2	19:05	0	0	0
6	1	17:30	0.0325	0	-0.0475
7	1	17:30	0.0175	-	-
7	2	19:05	0.075	-	-

From Table 3.8, we can see person 1 and person 2 both paticipate in their mandatory activities. Person 1 takes vehicle 1 while person 2 takes vehicle 2. Table 3.9 shows that person 2 is able to spend the maximum amount of time 570 minutes in activity 2 while Person 1 can only spend 415 minutes on activity 1 because Person 1 is assigned to particiate in activity 3 for 80 minutes. Person 1 arrives at destination 1 at time 8:20 which is the peak time (8:20) because this will yield the maximum utitily gain on arrival time. Person 2 also arrives at the peak time 9:00 for the same reason. In this example, the scale of utility (coefficient in Table 3.2 and Table 3.3) on arrival time is higher than that for activity duration; thus, person 1 can spend only 415 and 80 minutes at activities 1 and 3, respectively, in order to obtain the maximum arrival utility from arriving at peak preferred times for those activities. Compared to the orginal HAPP, UHAPP can take consideration of the utility for arrival time and utility for activity duration. Because there is no consideration of utility of arrival time and utility on duration, the solution in original HAPP assigns person 1 to undertake activity 3 before paticipating in activity 1 and the duration of every activity is known before running the model. Unlike HAPP, arrival times in the UHAPP model are not determined by the hard time windows. Instead, people will try to arrive at the peak hours if other constraints are satisfied. Activity duration is determind after running UHAPP and with consideration of activity chaining and activity assignment, the best activity duration will be assigned to each person. To better illustrate the activity gain for paticipating each activity, we illustrate the utility gain from activity arrival in Figure 3.3 and from activity druation in Figure 3.4, respectively for person 1.

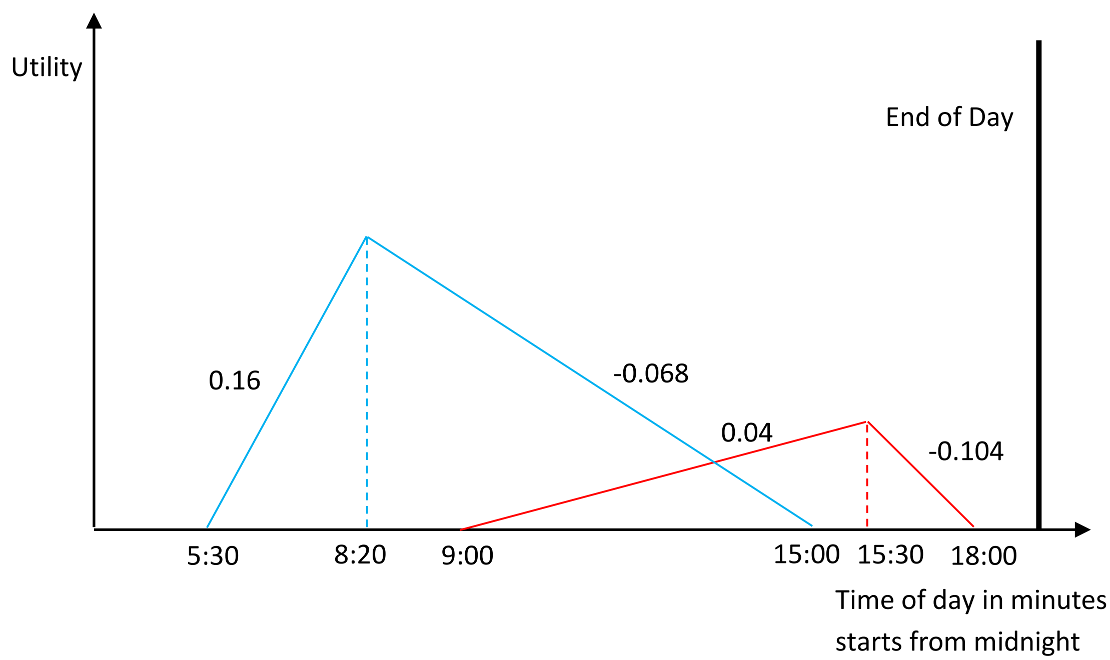

Figure 3.3 Arrival utility on activity 1 (blue) and activity 3 (red) of person 1

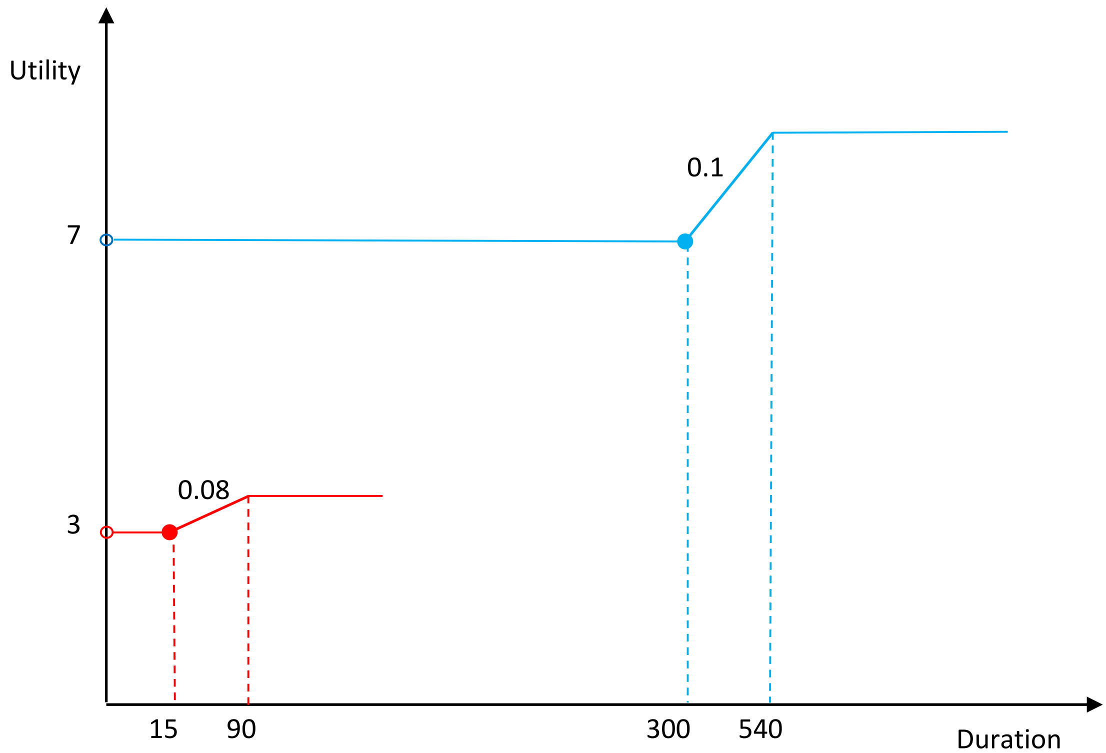

Figure 3.4 Duration utility on activity 1 (blue) and activity 3 (red) of person 1

To see how the arrival time utility function will affect people's travel decisions, let's change Person 1's μ_1^1 from 8:20 to 10:00, which means person 1 has a later arrival preference than before. Also, assuming the peak utility of activity 1 arrival remains the same, we change K_{1e}^1 to 0.1 and K_{1l}^1 to -0.09 (see Figure 3.5 and Table 3.10). We name this input as the case 1 senario. After 13465 MIP simplex iterations and 4049 branch-and-bound nodes running in AMPL, we have a new objective -29.1875. New solutions (Table 3.11 and Table 3.12) show that person 1 is not assigned to participate in activity 3 anymore (see Table 3.12). Instead, person 1 spends the maximum amount of time (540 minutes) at activity 1 and arrives home later at 19:30, which is outside of the drop off node 4 arrival time window (15:00-18:40) due to the later arrival preference on activity 1. Person 2 is assigned to participate on activity 3 and spend 50 minutes on it while activity 2 is shortening to 395 minutes comparing to the maximum 570 minutes. Thus, UHAPP can predict how the change of one arrival time preference on one person will effect changes on each person in the whole household with respect to activity assignment, activity arrival time and activity duration.

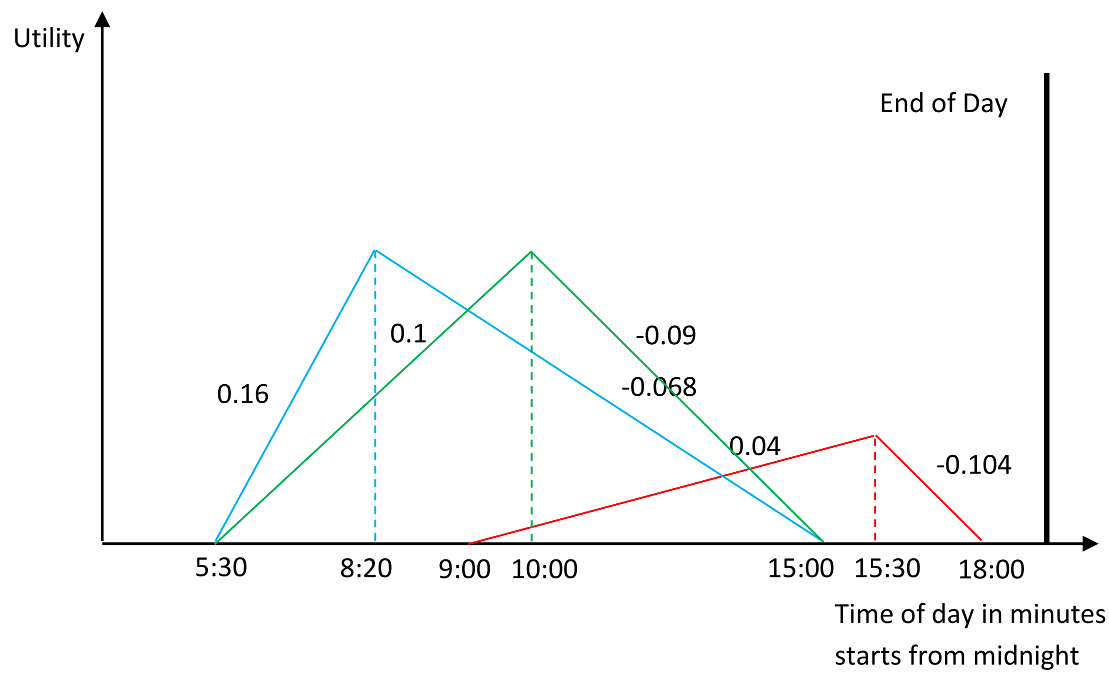

Figure 3.5 Arrival utility on old activity 1 (blue), new activity 1 (green) and activity 3 (red) of person 1

Table 3.10 Linear utility function of person on activity 1

Destination (i)	a_i^1	a_i^2	μ_i^1	μ_i^2	b_i^1	b_i^2	K_{ie}^1	K_{ie}^2	K_{il}^1	K_{il}^2
1	5:30	0	10:00	0	15:00	0	0.1	0	-0.09	0

Table 3.11 Vehicle flows and person flows from UHAPP case 1 scenario

Nodes (N)	Nodes (N)	Vehicles(V)	Persons (η)	X_{ij}^1	X_{ij}^2	H_{ij}^1	H_{ij}^2
0	1	1	1	1	0	1	0

0	2	2	2	0	1	0	1
1	4	1	1	1	0	1	0
2	3	2	2	0	1	0	1
3	5	2	2	0	1	0	1
4	7	1	1	1	0	1	0
5	6	2	2	0	1	0	1
6	7	2	2	0	1	0	1

Table 3.12 Arrival time and activity duration from UHAPP case 1 scenario

Nodes (N)	Person (η)	$\mathbf{T_i^{\alpha}}$	$\mathbf{T_i^{\alpha}.RC}$	$\mathbf{S_i^{\alpha}}$	$\mathbf{S_i^{\alpha}.RC}$
0	1	9:30	0	-	-
0	2	8:25	0	-	-
1	1	10:00	0	540	0
2	2	9:00	0	395	0
3	2	16:00	0.06	50	0
4	1	19:30	0	0	0
5	2	19:10	0	0	-0.02625
6	2	17:30	0.02625	0	0
7	1	19:30	0.06	-	-
7	2	18:00	0	-	-

To see how the utility of duration of one activity for one person will affect the arrival times and duration of other activities and other persons, let's change K_{1s}^{1} from 0.1 to 0.12 (see Figure 3.6 and Table 3.13), and all other inputs remain the same (Table 3.2 and Table 3.3). We name this input as case 2 scenario. After 7670 MIP simplex iterations and 1897 branch-and-bound nodes running in AMPL, we have a new objective -16.6875. The solutions are as shown in Table 3.14 and Table 3.15. As increasing one minute duration of activity 1 has more utility than before (an increase to 0.12 from 0.1), the duration of activity 1 correspondingly has been increased from 415 minutes to 540 minutes, which is the maximum utility of duration of activity 1. Also, activity 3 is assigned to person 2 for 50 minutes and the duration on activity 2 has been reduced to 395 minutes. Thus, compared to the hazard-based duration model (Bhat, A hazard-based duration model of shopping activity with nonparametric baseline specification and nonparametric control for unobserved heterogeneity, 1996), which is used prevalently in activity-based modeling, UHAPP offers a more explicit comparison of how duration of one activity of one person affects the household activity assignment, activity chaining, activity arrival time and activity duration with consideration of time and space constraints.

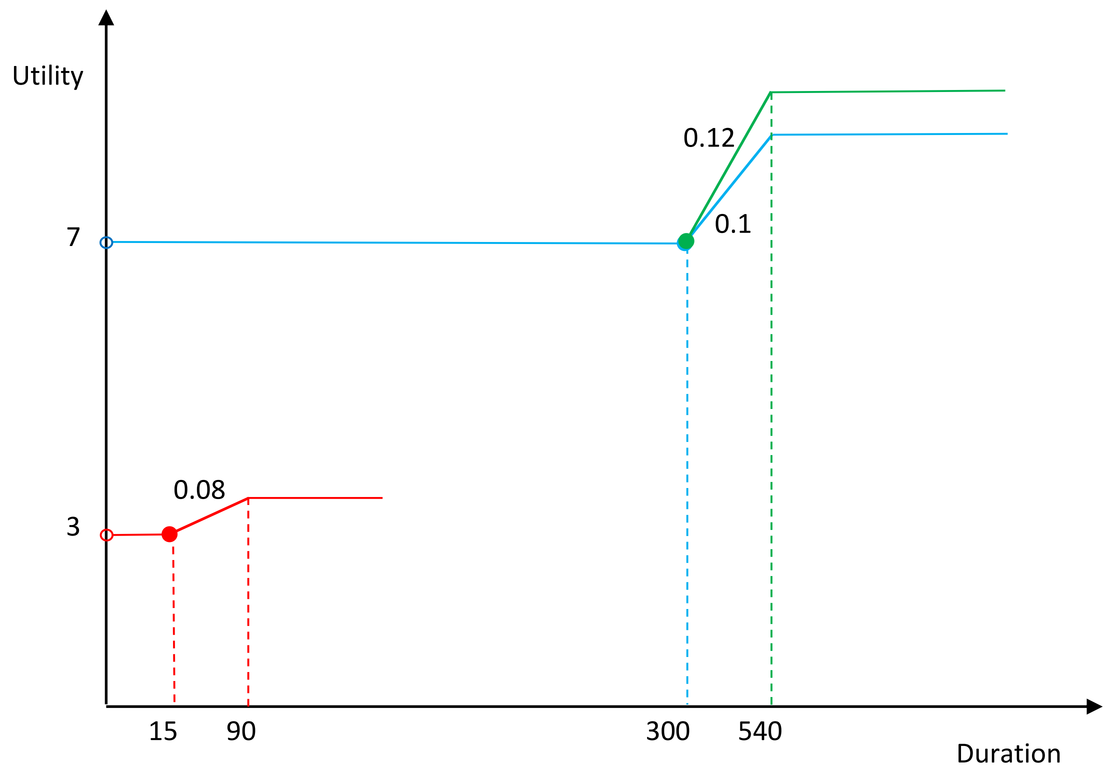

Figure 3.6 Duration utility on old activity 1 (blue), new activity 1 (green) and activity 3 (red) of person 1

Table 3.13 Utility function of duration $U_i^{\alpha\_min}$, $s_{i\_min}^{\alpha}$, $s_{i\_max}^{\alpha}$ and K_{is}^{α}

Activity (i)	$U_{i\_min}^1$	$U_{i\_min}^2$	$s_{i\_min}^1$	$s_{i\_min}^2$	$s_{i\_max}^1$	$s_{i\_max}^2$	K_{is}^1	K_{is}^2
1	7	0	300	0	540	0	0.12	0
2	0	7	0	360	0	570	0	0.12
3	3	3	15	20	90	120	0.08	0.06

Table 3.14 Vehicle flows and person flows from UHAPP case 2 scenario

Nodes (N)	Nodes (N)	Vehicles(V)	Persons (η)	X_{ij}^1	X_{ij}^2	H_{ij}^1	H_{ij}^2
0	1	1	1	1	0	1	0
0	2	2	2	0	1	0	1
1	4	1	1	1	0	1	0
2	3	2	2	0	1	0	1
3	5	2	2	0	1	0	1
4	7	1	1	1	0	1	0
5	6	2	2	0	1	0	1
6	7	2	2	0	1	0	1

Table 3.15 Arrival time and activity duration from UHAPP case 2 scenario

NODES (N)	Persons (η)	T_i^α	$T_i^\alpha.RC$	S_i^α	$S_i^\alpha.RC$
0	1	7:50	0	-	-
0	2	8:25	0	-	-
1	1	8:20	0	540	0
2	2	9:00	0	395	0
3	2	16:00	0.06	50	0
4	1	17:50	0	0	0
5	2	17:30	0	0	-0.02625
6	2	17:30	0.02625	0	0
7	1	17:50	0.06	-	-
7	2	18:00	0	-	-

To see how different weights on the objective function will affect peoples' travel decision, we change the uniform utility component weights to $\beta_{1i} = \beta_2 = \beta_3 = \beta_4 = 1$, $\beta_{5i} = 2$, which means that this household puts more weight on the utility of activity duration. We keep all other inputs the same as base case scenario. We name this input as case 3 scenario. We run UHAPP in AMPL calling CPLEX 12.5.1. After 7547 MIP simplex iterations and 2545 branch-and-bound nodes, we have a new objective 44.925. We have a positive optimal objective value after increasing the relative weight of the utility on activity duration—ostensibly the objective would be required to be positive if the household were to be assumed economically rational. The solutions are as shown in Table 3.16 and Table 3.17. Since this household considers the utility of activity duration as more important, we can see every person participates in each activity at its maximum duration and the arrival time has been shifted to obtain such a solution. These results indicate that further attention needs to be paid to choose/estimate an appropriate set of weights on each objective. Because the betas are subjective to different persons, we have further discussion related to betas in Chapter 5.

Table 3.16 Vehicle flows and person flows from UHAPP case 3 scenario

Nodes (N)	Nodes (N)	Vehicles(V)	Persons (η)	X_{ij}^1	X_{ij}^2	H_{ij}^1	H_{ij}^2
0	1	1	1	1	0	1	0
0	2	2	2	0	1	0	1
1	3	1	1	1	0	1	0
2	5	2	2	0	1	0	1
3	4	1	1	1	0	1	0
4	6	1	1	1	0	1	0
5	7	2	2	0	1	0	1
6	7	1	1	1	0	1	0

Table 3.17 Arrival time and activity duration from UHAPP case 3 scenario

NODES (N)	Persons (η)	T_i^α	$T_i^\alpha.RC$	S_i^α	$S_i^\alpha.RC$
0	1	5:45	0	-	-
0	2	8:25	0	-	-
1	1	6:15	0	540	0
2	2	9:00	0	570	0
3	1	15:30	0.0375	90	0
4	1	17:40	0	0	0
5	2	19:05	0	0	0
6	1	17:40	0.0325	0	-0.09

7	1	17:40	0.06	-	-
7	2	19:05	0.075	-	-

We combine solutions from HAPP as well as solutions from UHAPP in base case, case1, case 2 and case 3 in Table 3.18. In addition to what we have shown in Table 3.18, we also run several cases and we find out because the original HAPP has limitations on estimating arrival time and activity duration, we will not see differences in solutions as long as we do not change the arrival time windows and known activity duration. Because UHAPP has incorporated utility functions with respect to activity arrival and activity duration, by changing different peak arrival times, and coefficients defining the linear utility functions associated with arrival times and durations, as well as coefficients on objective function, UHAPP will generate different solutions (Table 3.18). According to our experiments, changing the (statistical) mode of arrival times as well as the lower bound and upper bound of the activity duration will significantly affect the arrival time solution. This suggests that policy makers address transportation policies that will diversify people's peak arrival time to activities. The coefficients defining the linear utility functions as well as the values of weighting coefficients of the terms of the objective function play a lesser role in changing activity arrival times and activity durations. This limitation comes from the rough time interval linearity assumption on the utility activity arrival function and utility duration function. Because in our examples there is only one K_{ie}^{α}, K_{il}^{α} and K_{is}^{α} to generate the optimal solution, like many linear programming problems, the optimal solution will always happen at the corners of the feasible region. For a long time interval, if there is only one K_{ie}^{α}, K_{il}^{α} and K_{is}^{α}, the sensitivity on activity arrival and activity duration is lost as these are continuous variables. Although UHAPP has extended unique solutions compared to the original HAPP, more unique solutions can be introduced by having more K_{ie}^{α}, K_{il}^{α} and K_{is}^{α}, which means we should divide smaller time intervals to have more lines to maintain piecewise linearity, or to more extreme, they will become non-linear functions. How changes of coefficients of K_{ie}^{α}, K_{il}^{α} and K_{is}^{α} throughout the full horizon will affect every single unit change on solutions on activity arrival time and activity duration may be ascertained through specification of β_i^{α}. β_i^{α} is only another version of changing K_{ie}^{α}, K_{il}^{α} and K_{is}^{α}. If we divide the objective function small enough, we may not need to have β_i^{α} because β_i^{α} can be calibrated within K_{ie}^{α}, K_{il}^{α} and K_{is}^{α} as a multiplier.

Table 3.18 Arrival time and activity duration of different input in HAPP and UHAPP

NODES (N)	Original HAPP		UHAPP in base case		UHAPP in case 1		UHAPP in case 2		UHAPP in case 3	
	T_i^{α}	S_i^{α}	T_i^{α}	S_i^{α}	T_i^{α}	S_i^{α}	T_i^{α}	S_i^{α}	T_i^{α}	S_i^{α}
0	9:20	-	9:30	-	7:50	-	7:50	-	5:45	-
0	5:25	-	8:25	-	8:25	-	8:25	-	8:25	-
1	10:30	300	10:00	540	8:20	415	8:20	540	6:15	540
2	6:00	360	9:00	395	9:00	570	9:00	395	9:00	570
3	10:00	15	16:00	50	15:30	80	16:00	50	15:30	90
4	16:00	0	19:30	0	17:30	0	17:50	0	17:40	0
5	12:35	0	19:10	0	19:05	0	17:30	0	19:05	0
6	16:00	0	17:30	0	17:30	0	17:30	0	17:40	0
7	16:00	-	19:30	-	17:30	-	17:50	-	17:40	-
7	12:35	-	18:00	-	19:05	-	18:00	-	19:05	-

Conclusion

Here we build on the capabilities of HAPP to generate an extension, UHAPP, that evaluates simultaneously activity assignment, activity chaining, activity arrival time and activity duration. We use a piecewise (triangular) linear function as the arrival time utility function and a piecewise linear step function as the activity duration utility function. We have demonstrated how the solution will change when the arrival utility function and the activity duration function are changed, as well as the change based on the weights of the various components of the objective function. Our hypothetic examples show that using a single value for K_{ie}^{α}, K_{il}^{α} and K_{is}^{α} throughout the full horizon will limit the solution space (i.e., will result in the same corner solutions for a range of options), and that perhaps smaller time intervals should be applied to produce more continuous solutions. Even nonlinear functions can be considered in order to have a full set of K_{ie}^{α}, K_{il}^{α} and K_{is}^{α} throughout the full horizon. Although the current format of UHAPP may work well for some highly homogeneous groups, we believe that inhomogeneous behaviors are more common in day to day basis. Well-calibrated arrival utility functions, activity duration functions and the weights of each objective are essential for practical application of our analysis. We have extended the capability of handling demand on HAPP. The next chapter will extend HAPP on the supply side by extending its capability of handling time-of-day traffic congestion.

Chapter 4 A TRAFFIC DEPENDENT HOUSEHOLD ACTIVITY PATTERN PROBLEM MODEL

Introduction

In Chapter 3, we extended the HAPP formulation to include the consideration of utility of activity arrival time and the utility of activity duration, in which we expand/eliminate time window constraints along with changing the objective function of HAPP to include the utility of the activities performed (rather than simply the disutility of travel, as in the original formulation of HAPP)—UHAPP. However, to consider different traffic conditions on peoples' activity scheduling, chaining and duration, we need to further extend UHAPP to handle time-dependent traffic conditions that may result in the scheduling of activities to avoid traffic congestion. In this chapter, a traffic-dependent utility- based household activity pattern problem (TUHAPP) model is proposed to address changes in travel behavior due to changes in travel time and travel cost during a day. TUHAPP provides a tool to analyze people's decisions regarding activity chaining, scheduling, and mode choice under consideration of the evolving traffic conditions during the day. Our hypothetical examples will show that TUHAPP is capable of being an operational activity-based demand modeling tool for planning agencies for meeting the transition to activity-based demand modeling in evaluating such policy changes as congestion pricing on existing facilities and other improvements that depend on sensitivity of peoples' travel decisions on different travel times and travel costs throughout a day.

Previous research related to HAPP has failed to take into account differences of travel time and travel cost during the day—HAPP can handle only a single (static) travel time and travel cost matrix throughout the day as the input. In reality, travel times and travel costs are time dependent during the day, as there are peak hours and off peak hours of traffic as many traffic management systems and transportation pricing schemes work on the time of day mechanism, activity-based models like HAPP should be able to accommodate changes of traffic during a day on people's travel decision. Furthermore, as originally formulated, HAPP focuses only on one travel mode (auto), preventing consideration of options of many people's travel decision in terms of mode choice. To address these limitations of HAPP, here we propose a traffic-dependent utility based household activity pattern problem (TUHAPP) model that can reflect changes in travel behavior due to changes in travel time and travel cost during the day; we further include explicit consideration of travel modes other than auto. We treat the travel time and travel cost as an aggregate zone-to-zone travel time and travel cost, which means we do not consider the detail of exact travel time from door to door for each mode. For example, for auto travel modes, we do not consider how long the vehicle stops in one intersection or if the driver is an aggressive driver who changes lane as much as possible to get to the destination. For public transit modes, we do not consider which stop the person chooses to get on the bus or get off the train, or whether this person drives to the bus station or somebody drops him/her off. We assume these data are available at the level of aggregate zone-to-zone travel times and travel costs data by mode because they are usually available at the current 4-step model. Figure 4.1 shows the dimension of travel time and travel cost compared to the original form of HAPP (in yellow color), which only tackles one travel time and one travel cost throughout the day. Figure 4.2 shows the hypothetical change of travel times and travel costs during the day with the approximation of the data input for HAPP and TUHAPP. Compared to the original form of HAPP, which can only tackle one travel time and one travel cost throughout the day, TUHAPP can tackle as many time periods of travel times and travel costs as long as data are available.

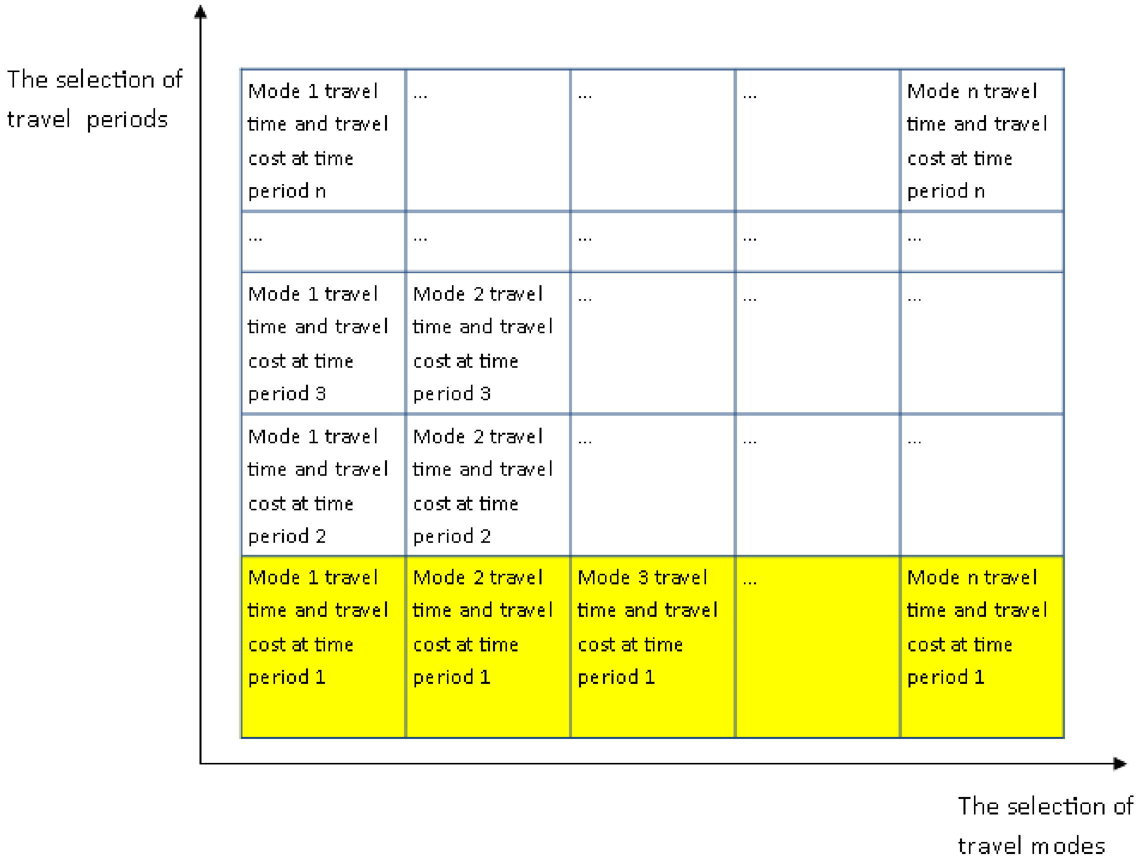

Figure 4.1 the dimension of travel time or travel cost matrixes

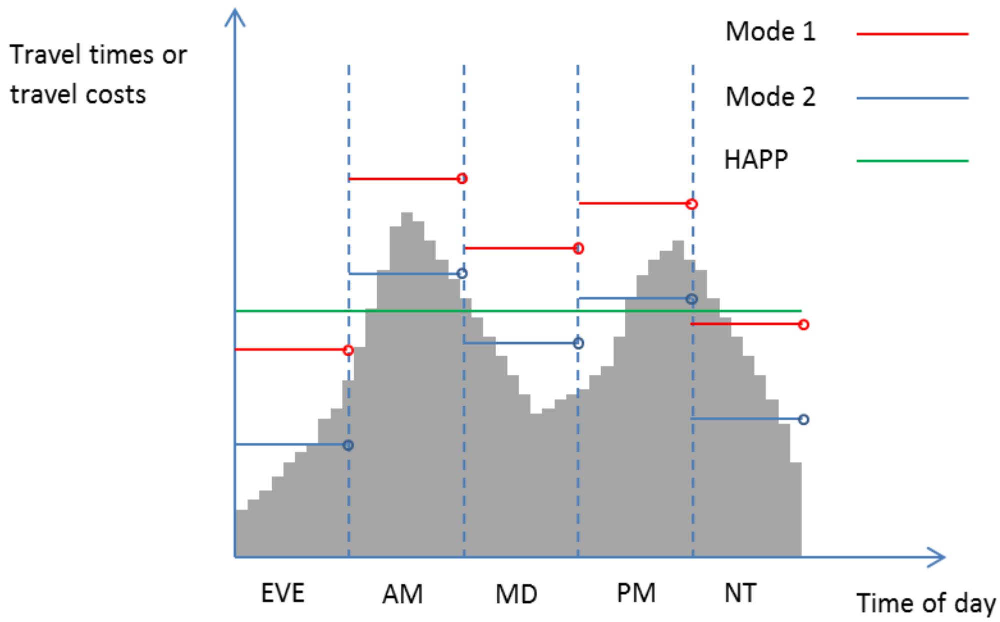

Figure 4.2 the time of day travel times and travel costs

Model formulation

We adopt the notation from Chapter 3. The general formulation of TUHAPP is

$$Maximize\ U(\boldsymbol{X_i}) = \boldsymbol{\beta}_i' \cdot \boldsymbol{X_i} \tag{4-1}$$

$$\text{subject to } \boldsymbol{BX_i} \leq 0, \tag{4-2}$$

where

$\boldsymbol{X_i} = [\boldsymbol{X}^{vp} \quad \boldsymbol{H}^{\alpha p} \quad \boldsymbol{T}^{\alpha} \quad \boldsymbol{S}^{\alpha}]'$, $\boldsymbol{X^{vp}} = \left[X_{\boldsymbol{ij}}^{\boldsymbol{vp}} = \begin{Bmatrix}0\\1\end{Bmatrix}\right]$, $\boldsymbol{H^{\alpha p}} = \left[H_{\boldsymbol{ij}}^{\boldsymbol{\alpha p}} = \begin{Bmatrix}0\\1\end{Bmatrix}\right]$, $\boldsymbol{T^{\alpha}} = [T_i^{\alpha} \geq 0]$, $\boldsymbol{S^{\alpha}} = [S_i^{\alpha} \geq 0]$, $\boldsymbol{\beta_i} = [\beta_i^{\alpha}]$. X^{vp} is the decision variable on vehicle flow; $H^{\alpha p}$ is the decision variable on person flow; T^{α} is the decision variable on arrival time; S^{α} is the decision variable on activity duration; β_i^{α} is the weight of objective imposed by each person and each activity. Equation (4-1) and (4-2) define TUHAPP in matrix format. A detail version of TUHAPP is defined as follow.

$P = \{1, 2, \ldots, i, \ldots, n\}$	Set of consecutive periods
$V_A = \{1, 2, \ldots, v\}$	Set of available auto vehicles in the household
$V_T = \{v+1, v+2, .., v+\lvert\eta\rvert\}$	Set of available transit modes in the household
$V = V_A \cup V_T$	Set of available modes used by travelers in the household to complete their scheduled activities.
$\left[a_p, b_p\right], p \in P$	The time window for the period p
t_{ij}^{vp}	The travel time from the location of activity i to the location of activity j in time period p by mode v.
c_{uw}^{vp}	Travel cost from location of activity i to the location of activity j in time period p by mode v.
$X_{ij}^{vp}, i, j \in N, v \in V, i \neq j$	Binary decision variable equal to unity if mode v travels from activity i to activity j in time period p, and zero otherwise.
$H_{ij}^{\alpha p}, i, j \in N, \alpha \in \eta, i \neq j$	Binary decision variable equal to unity if household member α travels from activity i to activity j in time period p, and zero otherwise.

Along with other notations in Chapter 3, the TUHAPP can be represented as

$$\begin{aligned} Max\ U = &\sum_{i \in D} \sum_{\alpha \in \eta} \beta_{1i}^{\alpha} f(T_i^{\alpha}) \sum_{j \in N} \sum_{p \in P} H_{ij}^{\alpha p} - \sum_{v \in V} \sum_{i \in N} \sum_{j \in N} \sum_{p \in P} t_{ij}^{vp} X_{ij}^{vp} \sum_{\alpha \in \eta} \beta_2^{\alpha} H_{ij}^{\alpha p} \\ &- \beta_3 \sum_{v \in V} \sum_{i \in O} \sum_{j \in L^+} \sum_{p \in P} K_v X_{ij}^{vp} - \sum_{v \in V} \sum_{i \in N} \sum_{j \in N} \sum_{p \in P} c_{ij}^{vp} X_{ij}^{vp} \sum_{\alpha \in \eta} \beta_4^{\alpha} H_{ij}^{\alpha p} \\ &+ \sum_{i \in L^+} \sum_{\alpha \in \eta} \beta_{5i}^{\alpha} g(S_i^{\alpha}) \sum_{j \in N} \sum_{p \in P} H_{ij}^{\alpha p} \end{aligned} \tag{4-3a}$$

Under the assumption that the utility functions for arrival time and duration do not vary over individuals, Equation (4-3a) becomes

$$Max\ U = \sum_{\alpha\in\eta}\sum_{i\in D}\sum_{j\in N}\sum_{p\in P}\beta_{1i} f(T_i^{\alpha}) H_{ij}^{\alpha p} - \beta_2 \sum_{v\in V}\sum_{i\in N}\sum_{j\in N}\sum_{p\in P} t_{ij}^{vp} X_{ij}^{vp}$$

$$- \beta_3 \sum_{v\in V}\sum_{i\in O}\sum_{j\in L^+}\sum_{p\in P} K_v X_{ij}^{vp} - \beta_4 \sum_{v\in V}\sum_{i\in N}\sum_{j\in N}\sum_{p\in P} c_{ij}^{vp} X_{ij}^{vp} \tag{4-3b}$$

$$+ \sum_{\alpha\in\eta}\sum_{i\in L^+}\sum_{j\in N}\sum_{p\in P}\beta_{5i}\, g(S_i^{\alpha}) H_{ij}^{\alpha p}$$

where $\sum_{\alpha\in\eta}\sum_{i\in D}\sum_{j\in N}\sum_{p\in P}\beta_{1i} f(T_i^{\alpha}) H_{ij}^{\alpha p}$ is the total utility of arrival time for the household, $\beta_2 \sum_{v\in V}\sum_{i\in N}\sum_{j\in N}\sum_{p\in P} t_{ij}^{vp} X_{ij}^{vp}$ is the total disutility of time spent traveling during the day, $\beta_3 \sum_{v\in V}\sum_{i\in O}\sum_{j\in L^+}\sum_{p\in P} K_v X_{ij}^{vp}$ is the total initial cost of using a vehicle for out of home activities. (As we mention before, we can include the parking cost for the other end of travel. We can even include time of day parking cost in TUHAPP, which is one of the hot topics in parking demand estimation, but for simplicity, we do not include parking cost in our following analysis) $\beta_4 \sum_{v\in V}\sum_{i\in N}\sum_{j\in N}\sum_{p\in P} c_{ij}^{vp} X_{ij}^{vp}$ is the total travel cost during the day; this includes any tolls, fuel consumption and other monetary costs. $\sum_{\alpha\in\eta}\sum_{i\in L^+}\sum_{j\in N}\sum_{p\in P}\beta_{5i}\, g(S_i^{\alpha}) H_{ij}^{\alpha p}$ is the total utility of time spent participating in the activity. The sum of these objective components is subject to the following constraints:

$$\sum_{v\in V}\sum_{p\in P}\sum_{j\in N} X_{ij}^{vp} = 1, \qquad i \in L^+ \tag{4-4}$$

$$\sum_{j\in N}\sum_{p\in P} X_{ij}^{vp} - \sum_{j\in N}\sum_{p\in P} X_{ji}^{vp} = 0, \qquad i \in L, v \in V \tag{4-5}$$

$$\sum_{j\in L^+}\sum_{p\in P} X_{0j}^{vp} \leq 1, \qquad v \in V \tag{4-6}$$

$$\sum_{j\in L^-}\sum_{p\in P} X_{j,2n+1}^{vp} \leq 1, \qquad v \in V \tag{4-7}$$

$$\sum_{j\in N}\sum_{p\in P} X_{j,i}^{vp} - \sum_{j\in N}\sum_{p\in P} X_{j,n+i}^{vp} = 0, \qquad i \in L^+, v \in V \tag{4-8}$$

$$X_{ij}^{vp} = \begin{cases} 0 \\ 1 \end{cases}; \quad i,j \in N, v \in V, p \in P \tag{4-10}$$

$$\sum_{j\in L^-} X_{0,j}^{vp} = 0, \qquad v \in V, p \in P \tag{4-11}$$

$$\sum_{i\in N} X_{i,0}^{vp} = 0, \qquad v \in V, p \in P \tag{4-12}$$

$$\sum_{i\in L^+} X_{i,2n+1}^{vp} = 0, \qquad v \in V, p \in P \tag{4-13}$$

$$\sum_{j\in N} X_{2n+1,j}^{vp} = 0, \qquad v \in V, p \in P \tag{4-14}$$

$$\sum_{i\in L^+} X_{i+n,i}^{vp} = 0, \qquad v \in V, p \in P \tag{4-15}$$

$$\sum_{j\in N} X_{j,j}^{vp} = 0, \qquad v \in V, p \in P \tag{4-16}$$

$$X_{i,j}^{vp} + X_{j,i}^{vp} \leq 1, \qquad i,j \in L^-, v \in V, p \in P \tag{4-17}$$

$$\sum_{\alpha\in\eta}\sum_{j\in N}\sum_{p\in P} H_{ij}^{\alpha p} = 1, \qquad i \in L^+ \tag{4-18}$$

$$\sum_{j\in N}\sum_{p\in P} H_{ij}^{\alpha p} - \sum_{j\in N}\sum_{p\in P} H_{ji}^{\alpha p} = 0, \qquad i \in L, \alpha \in \eta \tag{4-19}$$

$$\sum_{j\in L^+}\sum_{p\in P} H_{0j}^{\alpha p} \leq 1, \qquad \alpha \in \eta \tag{4-20}$$

$$\sum_{i\in L^-}\sum_{p\in P} H_{i,2n+1}^{\alpha p} \leq 1, \qquad \alpha \in \eta \tag{4-21}$$

$$\sum_{j\in N}\sum_{p\in P} H_{ji}^{\alpha p} - \sum_{j\in N}\sum_{p\in P} H_{j,n+i}^{\alpha p} = 0, \qquad i \in L^+, \alpha \in \eta \tag{4-22}$$

$$a_i - T_i^{\alpha} \leq \left(2 - \sum_{j\in L} H_{ij}^{\alpha p} - \sum_{j\in L} X_{ij}^{vp}\right) M, \qquad i \in L^+, j \in L, \alpha \in \eta, v \in V, p \in P \tag{4-23a}$$

$$T_i^{\alpha} - b_i \leq \left(2 - \sum_{j\in L} H_{ij}^{\alpha p} - \sum_{j\in L} X_{ij}^{vp}\right) M, \qquad i \in L^+, j \in L, \alpha \in \eta, v \in V, p \in P \tag{4-23b}$$

$$T_i^{\alpha} + S_i^{\alpha} + t_{i,n+i}^{vp} - T_{n+i}^{\alpha} \leq \left(2 - \sum_{k\in N} X_{k,i}^{vp} - \sum_{j\in N} H_{j,i}^{\alpha p}\right) M,$$

$$i \in L^+, \alpha \in \eta, v \in V, p \in P \tag{4-24}$$

$$T_i^{\alpha} + S_i^{\alpha} + t_{ij}^{vp} - T_j^{\alpha} \leq \left(2 - H_{ij}^{\alpha p} - X_{ij}^{vp}\right) M, \qquad i,j \in L, \alpha \in \eta, v \in V, p \in P \tag{4-25a}$$

$$T_i^{\alpha} + S_i^{\alpha} + t_{ij}^{vp} - T_j^{\alpha} \geq -\left(2 - H_{ij}^{\alpha p} - X_{ij}^{vp}\right) M, \qquad i,j \in L, \alpha \in \eta, v \in V, p \in P \tag{4-25b}$$

$$T_j^{\alpha} \leq \sum_{p\in P}\sum_{i\in N} H_{ij}^{\alpha p} M, \qquad j \in L, \alpha \in \eta, p \in P \tag{4-26}$$

$$S_j^{\alpha} \leq \sum_{p\in P}\sum_{i\in N} H_{ij}^{\alpha p} M, \qquad j \in L, \alpha \in \eta, p \in P \tag{4-27a}$$

$$S_i^{\alpha} \leq (1 - \sum_{j\in L^-} H_{ij}^{\alpha p}) M, \qquad i \in L^-, \alpha \in \eta, p \in P \tag{4-27b}$$

$$S_j^{\alpha} - s_{j\_min}^{\alpha} \geq \left(\sum_{p\in P}\sum_{i\in N} H_{ij}^{\alpha p} - 1\right) M, \qquad j \in L, \alpha \in \eta \tag{4-28}$$

$$T_0^{\alpha} + t_{0j}^{vp} - T_j^{\alpha} \leq \left(2 - H_{0j}^{\alpha p} - X_{0j}^{vp}\right) M, \qquad j \in L^+, \alpha \in \eta, v \in V, p \in P \tag{4-29a}$$

$$T_0^{\alpha} + t_{0j}^{vp} - T_j^{\alpha} \geq -\left(2 - H_{0j}^{\alpha p} - X_{0j}^{vp}\right) M, \qquad j \in L^+, \alpha \in \eta, v \in V, p \in P \tag{4-29b}$$

$$T_i^{\alpha} - T_{2n+1}^{\alpha} \leq \left(2 - H_{i,2n+1}^{\alpha p} - X_{i,2n+1}^{vp}\right)M, \qquad i \in L^-, \alpha \in \eta, v \in V, p \in P \tag{4-30}$$

$$f(T_i^{\alpha}) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ 0\ \leq T_i^{\alpha} < a_i^{\alpha} \tag{4-36a}$$

$$f(T_i^{\alpha}) = K_{ie}^{\alpha}(T_i^{\alpha} - a_i^{\alpha}), \qquad i \in L, \alpha \in \eta, \qquad if\ a_i^{\alpha}\ \leq T_i^{\alpha} \leq \mu_i^{\alpha} \tag{4-36b}$$

$$f(T_i^{\alpha}) = K_{il}^{\alpha}(T_i^{\alpha} - b_i^{\alpha}), \qquad i \in L, \alpha \in \eta, \qquad if\ \mu_i^{\alpha} < T_i^{\alpha} \leq b_i^{\alpha} \tag{4-36c}$$

$$f(T_i^{\alpha}) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ b_i^{\alpha} < T_i^{\alpha} \tag{4-36d}$$

$$f(T_{2n+1}^{\alpha}) = 0, \qquad \alpha \in \eta, \qquad if\ 0\ \leq T_{2n+1}^{\alpha} < a_{2n+1}^{\alpha} \tag{4-37a}$$

$$f(T_{2n+1}^{\alpha}) = K_{2n+1,e}^{\alpha}(T_{2n+1}^{\alpha} - a_{2n+1}^{\alpha}), \qquad \alpha \in \eta, \qquad if\ a_{2n+1}^{\alpha} \leq T_{2n+1}^{\alpha} \leq \mu_{2n+1}^{\alpha}, \tag{4-37b}$$

$$f(T_{2n+1}^{\alpha}) = K_{2n+1,l}^{\alpha}(T_{2n+1}^{\alpha} - b_{2n+1}^{\alpha}), \qquad \alpha \in \eta, \qquad if\ \mu_{2n+1}^{\alpha} < T_{2n+1}^{\alpha} \leq b_{2n+1}^{\alpha}, \tag{4-37c}$$

$$f(T_{2n+1}^{\alpha}) = 0, \qquad \alpha \in \eta, \qquad if\ b_{2n+1}^{\alpha} < T_{2n+1}^{\alpha}, \tag{4-37d}$$

$$g(S_i^{\alpha}) = 0, \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^{\alpha} = 0, \tag{4-38a}$$

$$g(S_i^{\alpha}) = U_{i\_min}^{\alpha}, \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^{\alpha} < s_{i\_min}^{\alpha}, \tag{4-38b}$$

$$g(S_i^{\alpha}) = U_{i\_min}^{\alpha} + K_{is}^{\alpha}\left(S_i^{\alpha} - s_{i\_min}^{\alpha}\right), \qquad i \in L, \alpha \in \eta, \qquad if\ s_{i\_min}^{\alpha} \leq S_i^{\alpha} < s_{i\_max}^{\alpha}, \tag{4-38c}$$

$$g(S_i^{\alpha}) = U_{i\_min}^{s} + K_{is}^{\alpha}\left(s_{i\_max}^{\alpha} - s_{i\_min}^{\alpha}\right), \qquad i \in L, \alpha \in \eta, \qquad if\ S_i^{\alpha} \geq s_{i\_max}^{\alpha}, \tag{4-38d}$$

$$\sum_{j \in L^-} H_{0,j}^{\alpha p} = 0, \qquad \alpha \in \eta, p \in P \tag{4-39}$$

$$\sum_{i \in N} H_{i,0}^{\alpha p} = 0, \qquad \alpha \in \eta, p \in P \tag{4-40}$$

$$\sum_{i \in L^+} H_{i,2n+1}^{\alpha p} = 0, \qquad \alpha \in \eta, p \in P \tag{4-41}$$

$$\sum_{j \in N} H_{2n+1,j}^{\alpha p} = 0, \qquad \alpha \in \eta, p \in P \tag{4-42}$$

$$\sum_{i \in L^+} H_{i+n,i}^{\alpha p} = 0, \qquad \alpha \in \eta, p \in P \tag{4-43}$$

$$\sum_{j \in N} H_{j,j}^{\alpha p} = 0, \qquad \alpha \in \eta, p \in P \tag{4-44}$$

$$H_{i,j}^{vp} + H_{j,i}^{vp} \leq 1, \qquad i,j \in L^{-}, v \in V, p \in P \tag{4-45}$$

$$\sum_{j \in \Omega_H^{\alpha}} \sum_{i \in L} \sum_{p \in P} H_{ij}^{\alpha p} = 0, \qquad \alpha \in \eta \tag{4-46}$$

$$H_{ij}^{\alpha p} = \begin{cases} 0 \\ 1 \end{cases}; \; i,j \in N, \alpha \in \eta, p \in P \tag{4-47}$$

$$\sum_{\alpha \in \eta} H_{ij}^{\alpha p} = \sum_{v \in V} X_{ij}^{vp}, \qquad i \in L, j \in L, p \in P \tag{4-48}$$

$$\sum_{\alpha \in \eta} H_{0j}^{\alpha p} = \sum_{v \in V} X_{0j}^{vp}, \qquad j \in L^{+}, p \in P \tag{4-49}$$

$$\sum_{\alpha \in \eta} H_{i,2n+1}^{\alpha p} = \sum_{v \in V} X_{i,2n+1}^{vp}, \qquad i \in L^{-}, p \in P \tag{4-50}$$

We incorporate the time period dependence to UHAPP by adding one time-of-day dimension to each vehicle flow and person flow. The following additional constraints are introduced to TUHAPP,

$$\sum_{p,q \in P:\, p<q} \sum_{k \in N} X_{jk}^{vp} \leq \left(1 - X_{ij}^{vq}\right) M, \qquad i \in N, j \in L, v \in V \tag{4-9}$$

$$\sum_{p,q \in P:\, p<q} \sum_{k \in N} H_{jk}^{\alpha p} \leq \left(1 - H_{ij}^{\alpha q}\right) M, \qquad i \in N, j \in L, \alpha \in \eta \tag{4-35}$$

$$a_p - (T_i^{\alpha} + S_i^{\alpha}) \leq \left(1 - H_{ij}^{\alpha p}\right) M, \qquad i,j \in L, \alpha \in \eta, p \in P \tag{4-31}$$

$$a_p - T_0^{\alpha} \leq \left(1 - H_{0j}^{\alpha p}\right) M, \qquad j \in L^{+}, \alpha \in \eta, p \in P \tag{4-32}$$

$$(T_i^{\alpha} + S_i^{\alpha}) - b_p \leq \left(1 - H_{ij}^{\alpha p}\right) M, \qquad i,j \in L, \alpha \in \eta, p \in P \tag{4-33}$$

$$T_0^{\alpha} - b_p \leq \left(1 - H_{0j}^{\alpha p}\right) M, \qquad j \in L^{+}, \alpha \in \eta, p \in P \tag{4-34}$$

Relationships (4-3)-(4-50) define the traffic-dependent utility based household activity pattern problem (TUHAPP). Compared to UHAPP in Chapter 3, constraints (4-9) and (4-35) are added to the constraints in UHAPP to force the condition that vehicle flows and person flows are time-period dependent. If a node has been visited, the visit has to have happened at least in the same or before the time period to which the next node belongs. Constraints (4-31)-(4-34) are added to assign the time window to each time period depending on availability of traffic condition data. The time windows of each time period are defined by transportation planning practice—common practice defines 4 or 5 time periods of a day—and the more time periods within a day, the longer it takes to obtain the optimal solution in TUHAPP.

Hypothetical example

To demonstrate how the change of travel times and travel costs during a day can affect peoples' travel decision, we generate a sample dataset based on Chapter 3's hypothetical example which includes a 2 person household with 2 automobile vehicles (V_1, V_2) and 1 transit mode (V_3, V_4) available. Here, the transit mode is identical for each person in the household. We divide the day into 1440 minutes. We keep the same input data from Table 3.1 to Table 3.3, but add an initial cost for transit mode in Table 4.1. We assign a lower initial cost to the 'transit mode' in this "baseline" example to see whether or not people change to the use of the transit mode because of this lower cost. We divide a day into 5 time periods based on traffic conditions in this example. Table 4.2 shows the time window for each time period. Table 4.3 and Table 4.4 are the travel time and travel cost tables for each mode in each time period. In the current example, they are the same for each mode in each time period.

Table 4.1 Initial cost of each mode

Modes (V)	K_v
1	10
2	10

3	5
4	5

Table 4.2 Periods time window

Periods (P)	Time window ($[a_p, b_p]$)	
1 (NT)	[0:01, 6:00]	[1, 360]
2 (AM)	[6:01, 9:00]	[361, 540]
3 (MD)	[9:01, 15:00]	[541, 900]
4 (PM)	[15:01, 19:00]	[901, 1140]
5 (EVE)	[19:01, 24:00]	[1141, 1440]

Table 4.3 Travel time matrix of every mode in every time period

NODES	0	1	2	3	4	5	6	7
0	0	30	35	40	0	0	0	0
1	30	0	20	15	30	30	30	30
2	35	20	0	25	35	35	35	35
3	40	15	25	0	40	40	40	40
4	0	30	35	40	0	0	0	0
5	0	30	35	40	0	0	0	0
6	0	30	35	40	0	0	0	0
7	0	30	35	40	0	0	0	0

Table 4.4 Travel cost matrix of every mode in every time period

NODES	0	1	2	3	4	5	6	7
0	0	3	3.5	4	0	0	0	0
1	3	0	2	1.5	3	3	3	3
2	3.5	2	0	2.5	3.5	3.5	3.5	3.5
3	4	1.5	2.5	0	4	4	4	4
4	0	3	3.5	4	0	0	0	0
5	0	3	3.5	4	0	0	0	0
6	0	3	3.5	4	0	0	0	0
7	0	3	3.5	4	0	0	0	0

We run TUHAPP model with these inputs in AMPL and call CPLEX 12.5.1. After 50546 MIP simplex iterations and 9835 branch-and-bound nodes, we have an optimal solution of -9.35. The total travel time is 155 minutes and the total travel cost is $15.50. The solutions for the vehicle flows and person flows are posted in Table 4.5. The solutions of arrival time and activity duration are posted in Table 4.6. Because travel time and travel cost of each pair of nodes are the same throughout the day, we obtain the same solution for the arrival times and durations as UHAPP base case scenario in Chapter 3. We also draw the travel diary of the household in Figure 4.3. The only difference is the optimal objective of -9.35 (compared to -19.35), because the transit mode has a lower initial cost—people in the household all use transit to complete all out of home activities. Thus, TUAHPP can evaluate mode choice by their aggregate zone-to-zone travel times and travel costs It takes longer (compared to using UHAPP) to obtain the optimal solution because the dimension of the problem is extended to include five time periods travel times and travel costs.

Table 4.5 Vehicle flows and person flows of TUHAPP example

Nodes (N)	Nodes (N)	Modes (V)	Persons (η)	Periods (P)	X_{ij}^3	X_{ij}^4	H_{ij}^1	H_{ij}^2
0	1	3	1	2	1	0	1	0
0	2	4	2	2	0	1	0	1
1	3	3	1	4	1	0	1	0
2	5	4	2	4	0	1	0	1
3	6	3	1	4	1	0	1	0
4	7	3	1	5	1	0	1	0
5	7	4	2	5	0	1	0	1
6	4	3	1	4	1	0	1	0

Table 4.6 Arrival time and activity duration of TUHAPP example

Nodes (N)	Persons (η)	T_i^{α}	S_i^{α}	Modes (V)	Periods (P)
0	1	7:50	-	3	2
0	2	8:25	-	4	2
1	1	8:20	415	3	2
2	2	9:00	570	4	2
3	1	15:30	80	3	4
4	1	17:30	0	3	4
5	2	19:05	0	4	5
6	1	17:30	0	3	4
7	1	17:30	-	3	4
7	2	19:05	-	4	5

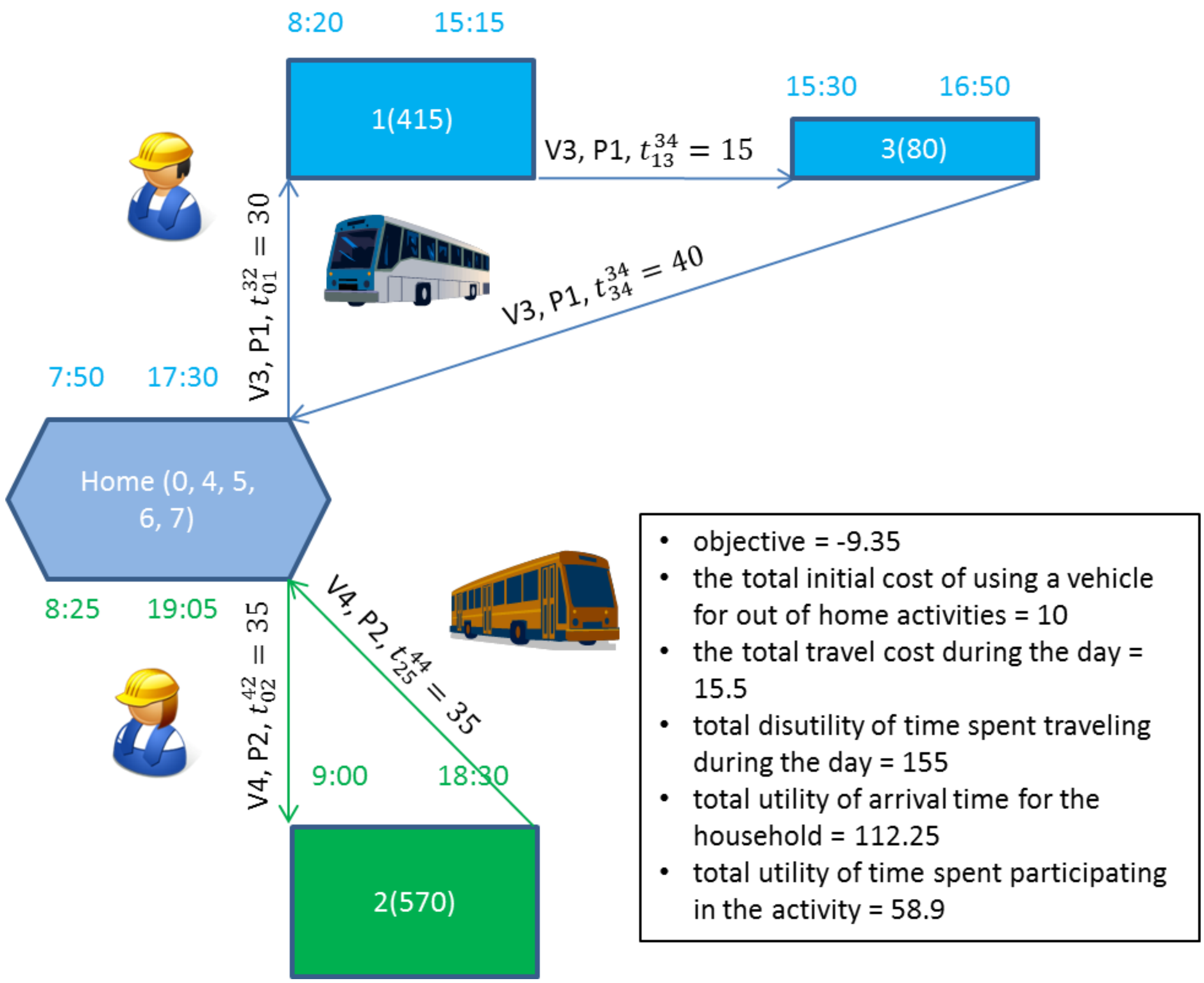

Figure 4.3 TUHAPP solution on hypothetical example

Input of different traffic conditions

Next, we change the travel times and travel costs for different time periods and different modes to see how travel time and travel cost differences during a day can change peoples' 'optimal' travel decisions. We compare two different transportation enhancement proposals (Table 4.7) affecting people's travel decisions on activity assignment, arrival times and activity durations in this demonstration. We assume that there is an enhancement to the transit network in proposal B.

This enhancement, for example, can be achieved either by increasing the frequency of the current transit service or by giving a higher signal priority to transit mode, which can result in a lower aggregate zone to zone travel times for transit mode. We assume that there is no improvement in the auto network in both proposals. Thus, scenarios for both proposals have the same travel time and travel cost for each pair of nodes for autos. The same transportation mode will have the same travel time and travel cost for each person. We also give both modes the same initial cost as shown in Table 4.8. Table 4.9, Table 4.10 and Table 4.11 list the travel time and travel cost of each mode in each period in Proposal A and Proposal B. The enhancement on Proposal B has a decrease only on the travel time for transit mode, while the travel costs are the same in both proposals.

Table 4.7 Two different transportation enhancement proposals

Proposal A	Proposal B
Basic transportation network	Enhancement on transit service, lower travel time on transit mode

Table 4.8 Initial cost of each mode

Modes (V)	K_v
1	10
2	10
3	10
4	10

Table 4.9 Travel time and cost matrix of mode auto in proposal A and proposal B

		Travel time matrix								Travel cost matrix							
NT	NODES	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
	0	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0

	1	30	0	20	15	30	30	30	30	3	0	2	1.5	3	3	3	3
	2	35	20	0	25	35	35	35	35	3.5	2	0	2.5	3.5	3.5	3.5	3.5
	3	40	15	25	0	40	40	40	40	4	1.5	2.5	0	4	4	4	4
	4	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	5	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	6	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	7	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
AM	**0**	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	1	60	0	40	30	60	60	60	60	3	0	2	1.5	3	3	3	3
	2	70	40	0	50	70	70	70	70	3.5	2	0	2.5	3.5	3.5	3.5	3.5
	3	80	30	50	0	80	80	80	80	4	1.5	2.5	0	4	4	4	4
	4	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	5	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	6	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	7	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
MD	**0**	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	1	30	0	20	15	30	30	30	30	3	0	2	1.5	3	3	3	3
	2	35	20	0	25	35	35	35	35	3.5	2	0	2.5	3.5	3.5	3.5	3.5
	3	40	15	25	0	40	40	40	40	4	1.5	2.5	0	4	4	4	4
	4	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	5	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	6	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	7	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
PM	**0**	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	1	60	0	40	30	60	60	60	60	3	0	2	1.5	3	3	3	3
	2	70	40	0	50	70	70	70	70	3.5	2	0	2.5	3.5	3.5	3.5	3.5
	3	80	30	50	0	80	80	80	80	4	1.5	2.5	0	4	4	4	4
	4	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	5	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	6	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
	7	0	60	70	80	0	0	0	0	0	3	3.5	4	0	0	0	0
EVE	**0**	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	1	30	0	20	15	30	30	30	30	3	0	2	1.5	3	3	3	3
	2	35	20	0	25	35	35	35	35	3.5	2	0	2.5	3.5	3.5	3.5	3.5
	3	40	15	25	0	40	40	40	40	4	1.5	2.5	0	4	4	4	4
	4	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	5	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	6	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0
	7	0	30	35	40	0	0	0	0	0	3	3.5	4	0	0	0	0

Table 4.10 Travel time and cost matrix of mode transit in proposal A

		Travel time matrix								Travel cost matrix							
	NODES	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
NT	**0**	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	1	60	0	40	30	60	60	60	60	2	0	2	2	2	2	2	2
	2	70	40	0	50	70	70	70	70	2	2	0	2	2	2	2	2
	3	80	30	50	0	80	80	80	80	2	2	2	0	2	2	2	2
	4	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
AM	**0**	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	1	36	0	24	18	36	36	36	36	2	0	2	2	2	2	2	2
	2	42	24	0	30	42	42	42	42	2	2	0	2	2	2	2	2
	3	48	18	30	0	48	48	48	48	2	2	2	0	2	2	2	2
	4	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
MD	**0**	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	1	60	0	40	30	60	60	60	60	2	0	2	2	2	2	2	2
	2	70	40	0	50	70	70	70	70	2	2	0	2	2	2	2	2
	3	80	30	50	0	80	80	80	80	2	2	2	0	2	2	2	2
	4	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
PM	**0**	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	1	36	0	24	18	36	36	36	36	2	0	2	2	2	2	2	2
	2	42	24	0	30	42	42	42	42	2	2	0	2	2	2	2	2
	3	48	18	30	0	48	48	48	48	2	2	2	0	2	2	2	2
	4	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	36	42	48	0	0	0	0	0	2	2	2	0	0	0	0
EVE	**0**	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	1	60	0	40	30	60	60	60	60	2	0	2	2	2	2	2	2
	2	70	40	0	50	70	70	70	70	2	2	0	2	2	2	2	2
	3	80	30	50	0	80	80	80	80	2	2	2	0	2	2	2	2

	4	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	60	70	80	0	0	0	0	0	2	2	2	0	0	0	0

Table 4.11 Travel time and cost matrix of mode transit in proposal B

		Travel time matrix								**Travel cost matrix**							
	NODES	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
NT	**0**	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	1	48	0	32	24	48	48	48	48	2	0	2	2	2	2	2	2
	2	56	32	0	40	56	56	56	56	2	2	0	2	2	2	2	2
	3	64	24	40	0	64	64	64	64	2	2	2	0	2	2	2	2
	4	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
AM	**0**	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
	1	28.8	0	19.2	14.4	28.8	28.8	28.8	28.8	2	0	2	2	2	2	2	2
	2	33.6	19.2	0	24	33.6	33.6	33.6	33.6	2	2	0	2	2	2	2	2
	3	38.4	14.4	24	0	38.4	38.4	38.4	38.4	2	2	2	0	2	2	2	2
	4	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
MD	**0**	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	1	48	0	32	24	48	48	48	48	2	0	2	2	2	2	2	2
	2	56	32	0	40	56	56	56	56	2	2	0	2	2	2	2	2
	3	64	24	40	0	64	64	64	64	2	2	2	0	2	2	2	2
	4	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
PM	**0**	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
	1	28.8	0	19.2	14.4	28.8	28.8	28.8	28.8	2	0	2	2	2	2	2	2
	2	33.6	19.2	0	24	33.6	33.6	33.6	33.6	2	2	0	2	2	2	2	2
	3	38.4	14.4	24	0	38.4	38.4	38.4	38.4	2	2	2	0	2	2	2	2
	4	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0

	5	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	28.8	33.6	38.4	0	0	0	0	0	2	2	2	0	0	0	0
EVE	**0**	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	1	48	0	32	24	48	48	48	48	2	0	2	2	2	2	2	2
	2	56	32	0	40	56	56	56	56	2	2	0	2	2	2	2	2
	3	64	24	40	0	64	64	64	64	2	2	2	0	2	2	2	2
	4	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	5	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	6	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0
	7	0	48	56	64	0	0	0	0	0	2	2	2	0	0	0	0

We run TUHAPP with Proposal A data and call CPLEX 12.5.1.0 in AMPL; after 30546 MIP simplex iterations and 8007 branch-and-bound nodes, we have an objective -39.175. The total travel time is 172 minutes and the total travel cost is 13 dollars. The solutions of vehicle flows and person flows are posted in Table 4.12. The solutions of arrival time and activity duration are posted in Table 4.13. Each household member’s choice of travel mode is based on their arrival time utility and the travel time on using that mode. Household member 1 chooses transit mode as the transportation mode and is assigned to perform activity 3. Because transit has a faster travel time during the time period 2 and time period 4, which can yield a lower total travel time for household member 1, household member 1 chooses to use transit to complete all his/her out of home activities. Because household member 2 chooses to use mode auto and time period 2 and time period 4 have longer travel times for auto vehicles, household member 2 chooses to depart at time period 3 (9:01) which has shorter travel times by auto vehicles. Figure 4.4 shows the optimal solutions travel agenda for this household in Proposal A transportation settings. Thus, TUHAPP captures the impact of changes in travel time by time of day and by mode which can significantly change peoples’ daily agenda compared to examples we have shown in Chapter 3.

Table 4.12 Vehicle flows and person flows in Proposal A

Nodes (N)	Nodes (N)	Modes (V)	Persons (η)	Periods (P)	X_{ij}^3	X_{ij}^2	H_{ij}^1	H_{ij}^2
0	1	3	1	2	1	0	1	0
0	2	2	2	3	0	1	0	1
1	3	3	1	4	1	0	1	0
2	5	2	2	5	0	1	0	1
3	6	3	1	4	1	0	1	0
4	7	3	1	5	1	0	1	0
5	7	2	2	5	0	1	0	1
6	4	3	1	4	1	0	1	0

Table 4.13 Arrival time and activity duration in Proposal A

Nodes (N)	Persons (η)	T_i^α	S_i^α	Modes (V)	Periods (P)
0	1	7:44	.	3	2
0	2	9:01	.	2	3
1	1	8:20	412	3	4
2	2	9:36	570	2	5
3	1	15:30	72	2	4
4	1	17:30	0	2	5
5	2	19:41	0	2	5
6	1	17:30	0	3	4
7	1	17:30	.	3	4
7	2	19:41	.	2	5

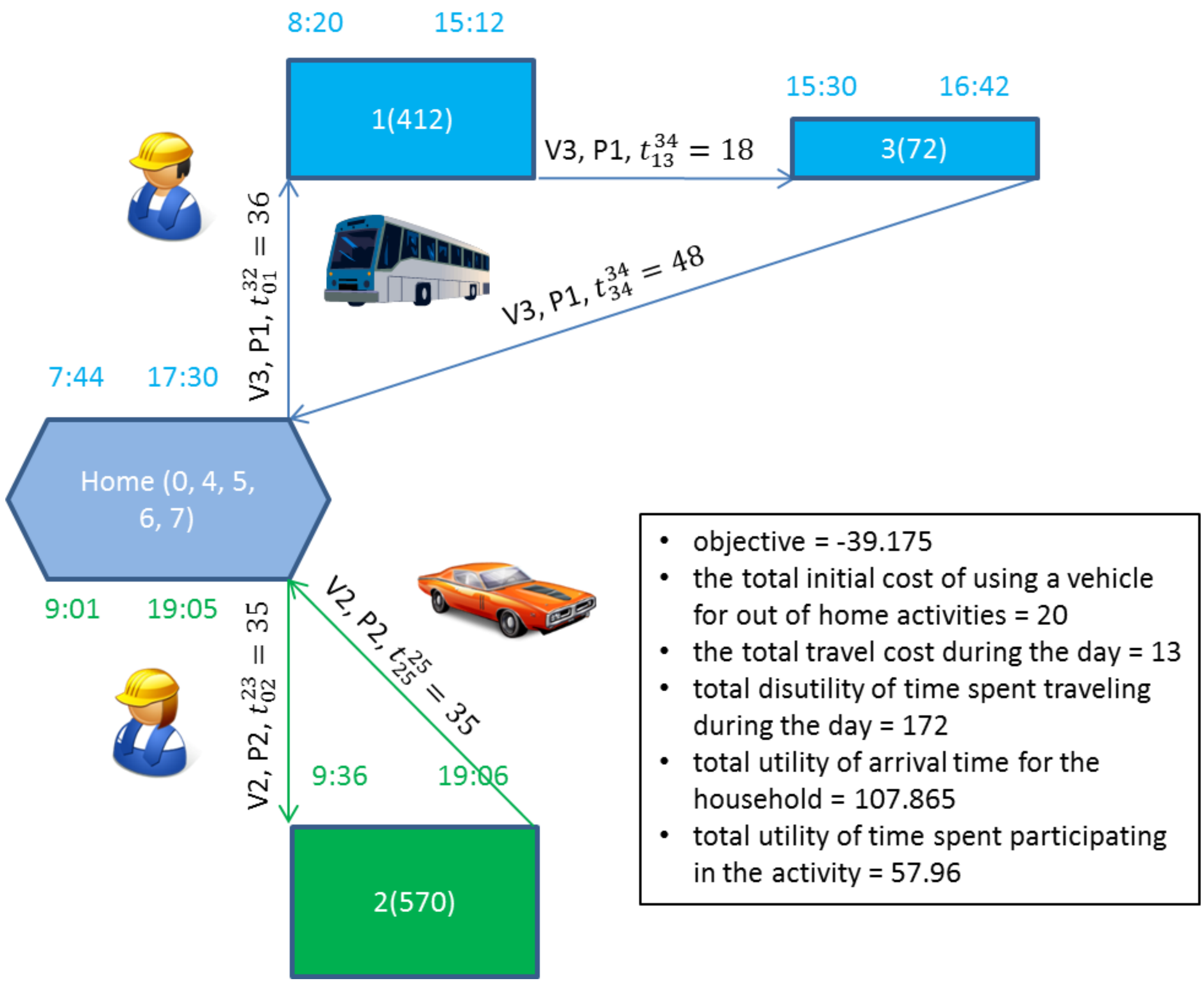

Figure 4.4 TUHAPP solution of proposal A

Similarly, we run TUHAPP with proposal B data and call CPLEX 12.5.1.0 in AMPL. After 7565 MIP simplex iterations and 1929 branch-and-bound nodes, we have an objective -7.357. Because of the improvement of transit service, the objective -7.357 of proposal B is greater than -39.715 of proposal A. The total travel time is 149 minutes (compared to 172 minutes) and the total travel cost is $10.00. The solutions of vehicle flows and person flows are posted in Table 4.14. The solutions of arrival time and activity duration are posted in Table 4.15. Not only do both members in the household use transit service to finish their out of home activities, the improvement of transit service has also changed the duration on activities 1 and 3 for person 1. The duration on activities 1 and 3 has been increased from 412 minutes to 416 minutes and from 72 minutes to 82 minutes, respectively. Also, person 2 can arrive at activity 2 at the peak hour 9:00 compared to using Proposal A transportation system. Figure 4.5 shows the optimal solutions of Proposal B. Thus, the improvement of transportation service on one mode will change this household's daily agenda as long as their daily life style is fixed. TUHAPP can evaluate how different transportation improvement alternatives affect people's daily agenda, so it can provide suggestions to policy makers regarding time-of-day congestion pricing and mode choice.

Table 4.14 Vehicle flows and person flows in Proposal B

Nodes (N)	Nodes (N)	Modes (V)	Persons (η)	Periods (P)	X_{ij}^3	X_{ij}^4	H_{ij}^1	H_{ij}^2
0	1	4	1	2	1	0	1	0
0	2	3	2	2	0	1	0	1
1	3	4	1	4	1	0	1	0
2	5	3	2	4	0	1	0	1
3	6	4	1	4	1	0	1	0
4	7	4	1	5	1	0	1	0
5	7	3	2	5	0	1	0	1
6	4	4	1	4	1	0	1	0

Table 4.15 Arrival time and activity duration in Proposal B

Nodes (N)	Persons (η)	T_i^α	S_i^α	Modes (V)	Periods (P)
0	1	7:51	.	4	2
0	2	8:26	.	3	2
1	1	8:20	416	4	2
2	2	9:00	570	3	2
3	1	15:30	82	4	4
4	1	17:30	0	4	4
5	2	19:03	0	3	5

6	1	17:30	0	4	4
7	1	17:30	.	4	4
7	2	19:03	.	3	5

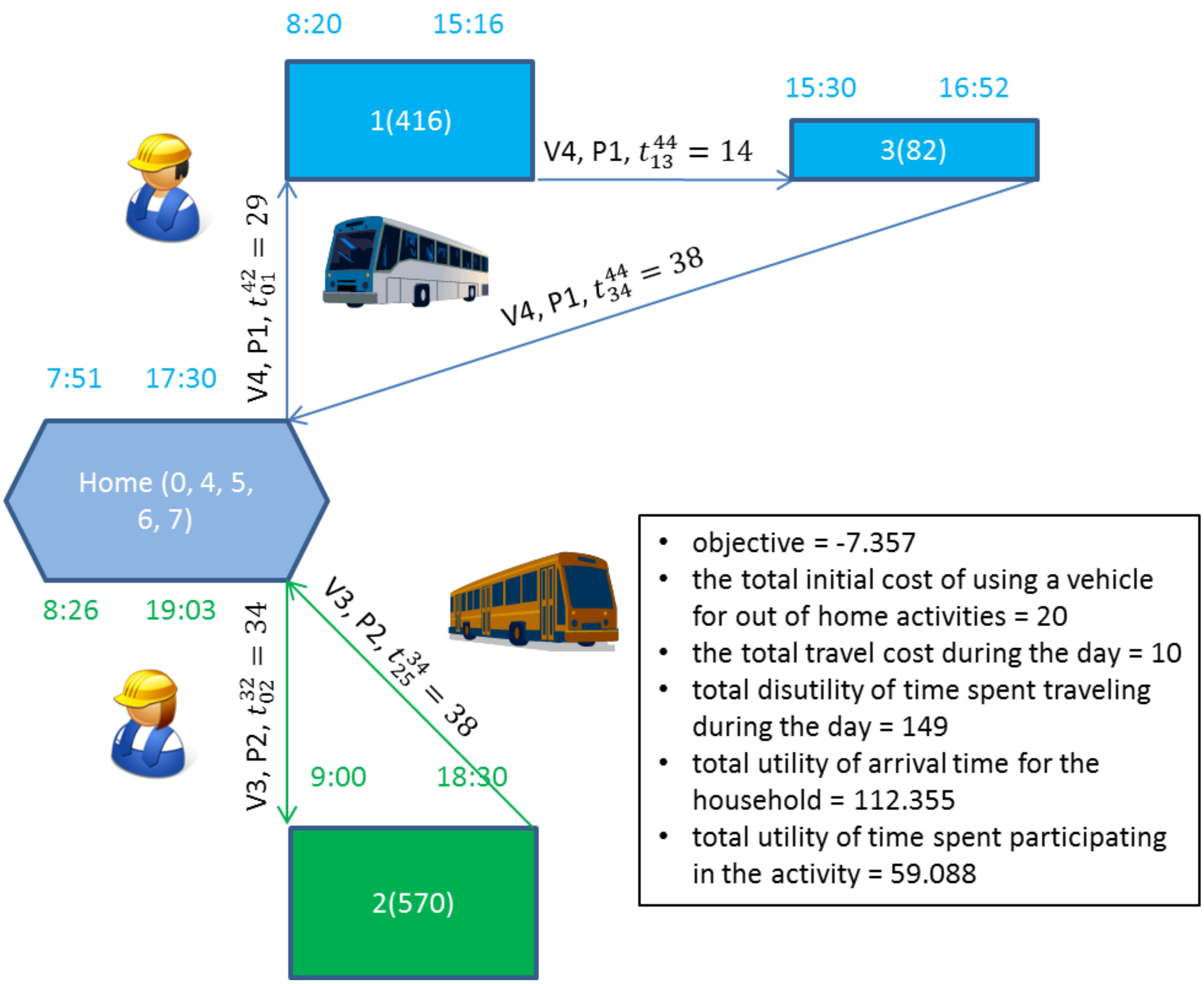

Figure 4.5 TUHAPP solution of proposal B

Conclusion

The original HAPP model can evaluate only one travel time and travel cost throughout the day. It cannot reflect changes in travel times and travel costs during the day on people's activity agenda.

By adding time-period traffic conditions into HAPP, we can evaluate different travel times and travels costs at different time periods to see how traffic congestion can actually change people's activity agenda. One of the key roles in activity-based demand modeling is to evaluate different time-of-day congestion pricing schemes in the network. Our hypothetical results demonstrate how lowering travel time on transit mode would be expected to encourage people to switch from auto vehicles to transit so that they can enjoy their activities longer (or maintain the same arrival time) by saving travel times. Compared to other activity-based models, TUHAPP can 'read' time-of-day traffic conditions so it can reflect policy changes affecting time-of-day pricing explicitly. However, because we use discontinuous step functions to represent the time-of-day travel times and travel costs, it could violate the 'first come first serve' rule. If there are dramatic decreases in travel times and travel costs between two consecutive time periods, this limitation will be severe.

So far, we have only tested TUHAPP (UHAPP) on hypothetical data. In the next chapter, we will use a household travel survey (as much as possible, depending on what data are available) to see how TUHAPP can fit into a regional activity-based demand modeling framework.

Chapter 5 Development of activity-based demand modeling framework

Introduction

Although we have developed the TUHAPP model such that it can reflect consideration of peoples' activity arrival time and activity duration preferences as well as interference between household members and time of day traffic conditions, and tested it on hypothetical data, the purpose of developing such a complicated model is for its application to forecasting people's travel decisions relative to transportation network and policy changes. This chapter proposes a procedure for using TUHAPP (UHAPP) as part of an activity-based modeling framework. Under known (or assumed) distributions of the demand of peoples' activities arrival times and durations, as well as the weight distributed of each objective component, the model can evaluate how conveniences or inconvenience resulting from transportation policy change will affect people's travel decisions with respect to: activity arrival time, activity assignment, activity duration, travel mode and scheduling. In this demonstration application, we use the 2001 SCAG household travel survey (HTS) data for estimating the distributions of activity arrival time preferences, activity duration functions and the relative utility weight of each objective. Here, we only provide the skim on how to use TUHAPP (UHAPP) in a practical real-world planning application because the data quality and some required data are missing; our results are significantly influenced by the data and the assumptions we make. Solutions obtained from TUHAPP (UHAPP) give options to stakeholders in making decisions, but we emphasize the limitations of our methodology. Figure 5.1 shows the input-output flow chart of TUHAPP (UHAPP) model.

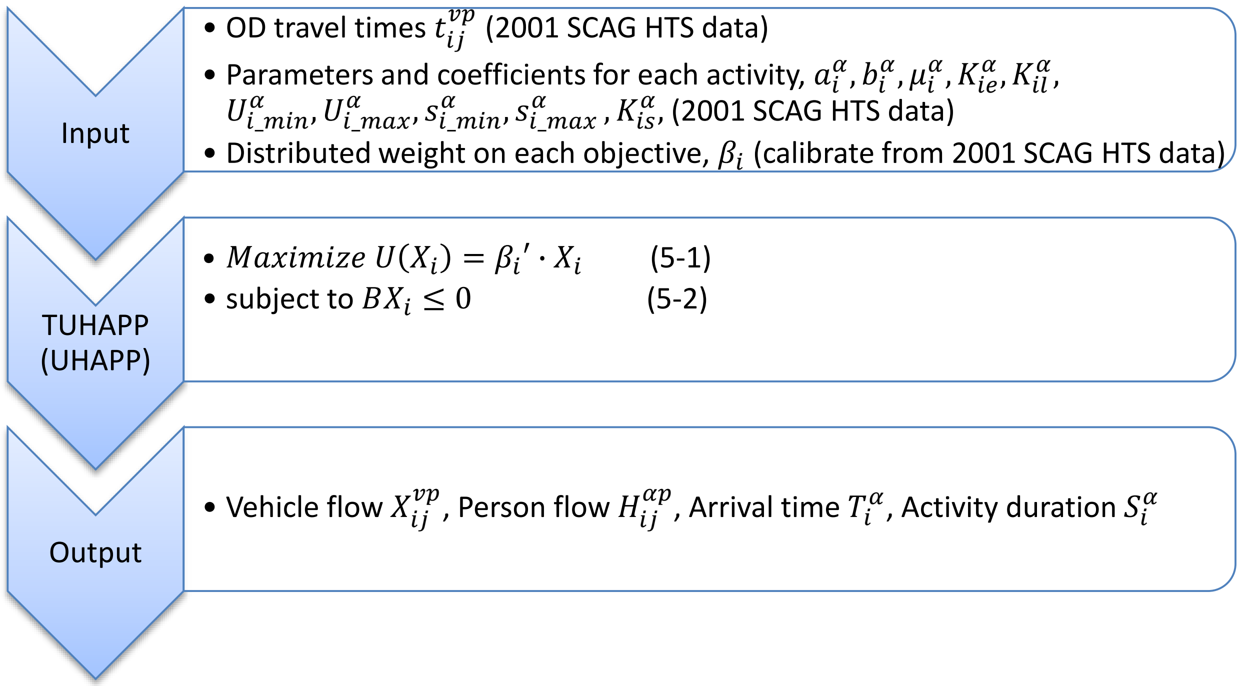

Figure 5.1 Structure of TUHAPP (UHAPP) Application

Survey data and activity pattern statistics

In previous chapters, we have demonstrated that TUHAPP (UHAPP) can handle activity scheduling and its interaction with activity duration and activity assignment under the time-of-day traffic conditions. However, without a statistical reference, what we have shown is based only on an arbitrary characterization of people's preferences with regard to activity arrival time and duration. To further demonstrate how TUHAPP (UHAPP) can be used as a regional transportation planning tool, we use the 2001 SCAG HTS data to establish a statistical reference for these preferences. The 2001 SCAG HTS data collection was conducted during Spring 2001, Fall 2001, and Spring 2002. The main data set contains 16,939 households distributed by county as follows:

Table 5.1 Data set households by county of residence

County	Number of households	Percent
Imperial	915	5.4
Los Angeles	7,262	42.9
Orange	2,316	13.7
Riverside	2,341	13.8
San Bernardino	2,172	12.8
Ventura	1,933	11.4
Total	16,939	100

The 16,939 sampled households were used to represent all 5,386,491 occupied housing units and 15,904,849 persons in the study area. More than 40 million trips were made within the SCAG region on an average weekday according to the survey.

There is no direct number of activities performed by each household in the survey. Instead, the survey uses number of trips to define household's daily activities. Figure 5.2 and Table 5.2 show that more than 75% of households have less than 10 trips per day. Figure 5.3 and Table 5.3 show that more than 95% of households in the region have fewer than 5 persons within the household. Figure 5.4 and Table 5.4 show that about 95% of households have fewer than 3 vehicles within the household. These statistics give us a general sense of the region. Thus, for simplicity reason, we define our research domain using the 75%, 95% and 95% samples as the total number of activities, number of household members, and number of available vehicles within a household, respectively, to represent this region.

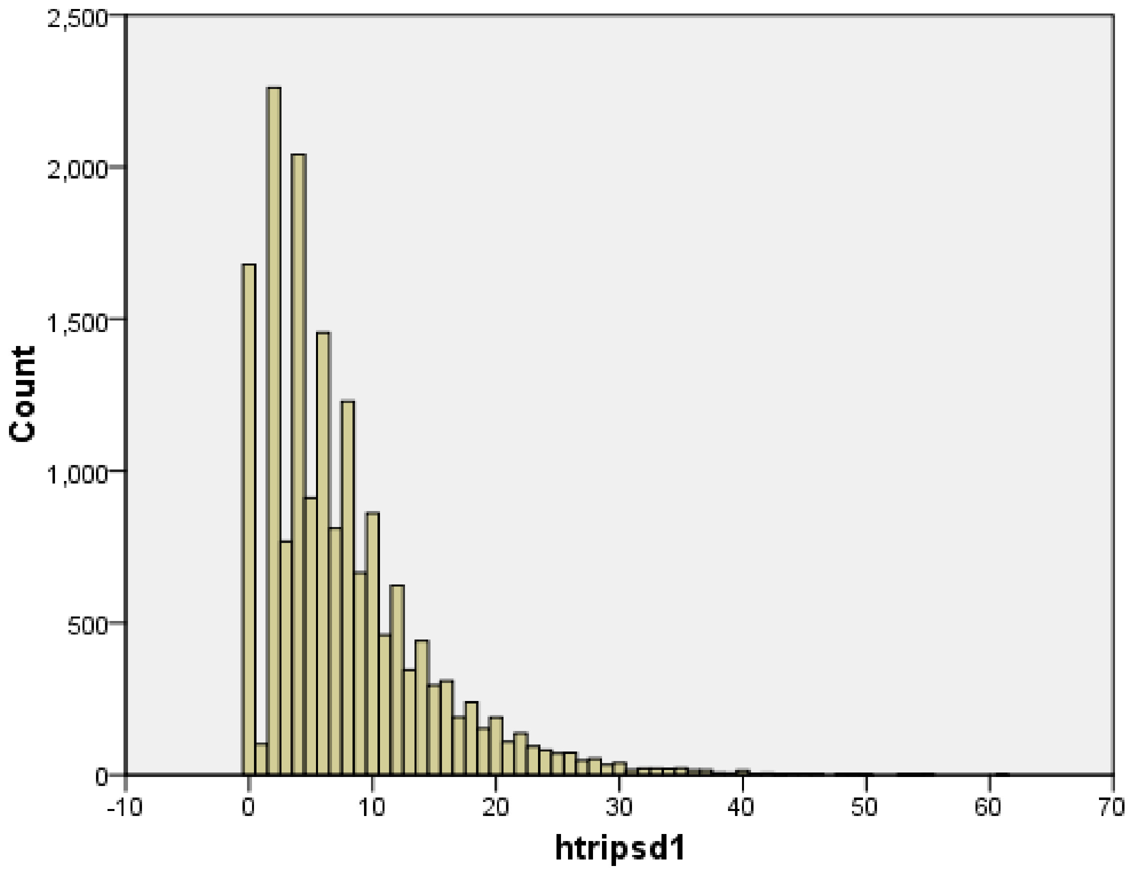

Figure 5.2 Distribution of number of trips of every household

Table 5.2 Number of trips

Number of trips	Counts	Percent	Cumulative Percent
0	1680	9.9	9.9
1	101	.6	10.5
2	2262	13.4	23.9
3	767	4.5	28.4
4	2042	12.1	40.5
5	911	5.4	45.8
6	1455	8.6	54.4
7	811	4.8	59.2
8	1229	7.3	66.5
9	665	3.9	70.4
10	861	5.1	75.5

11	460	2.7	78.2
12	623	3.7	81.9
13	345	2.0	83.9
14	441	2.6	86.5
15	295	1.7	88.2
16	309	1.8	90.1
17	189	1.1	91.2
18	238	1.4	92.6
19	152	.9	93.5
>=20	1103	6.5	100
Total	16939	100.0	

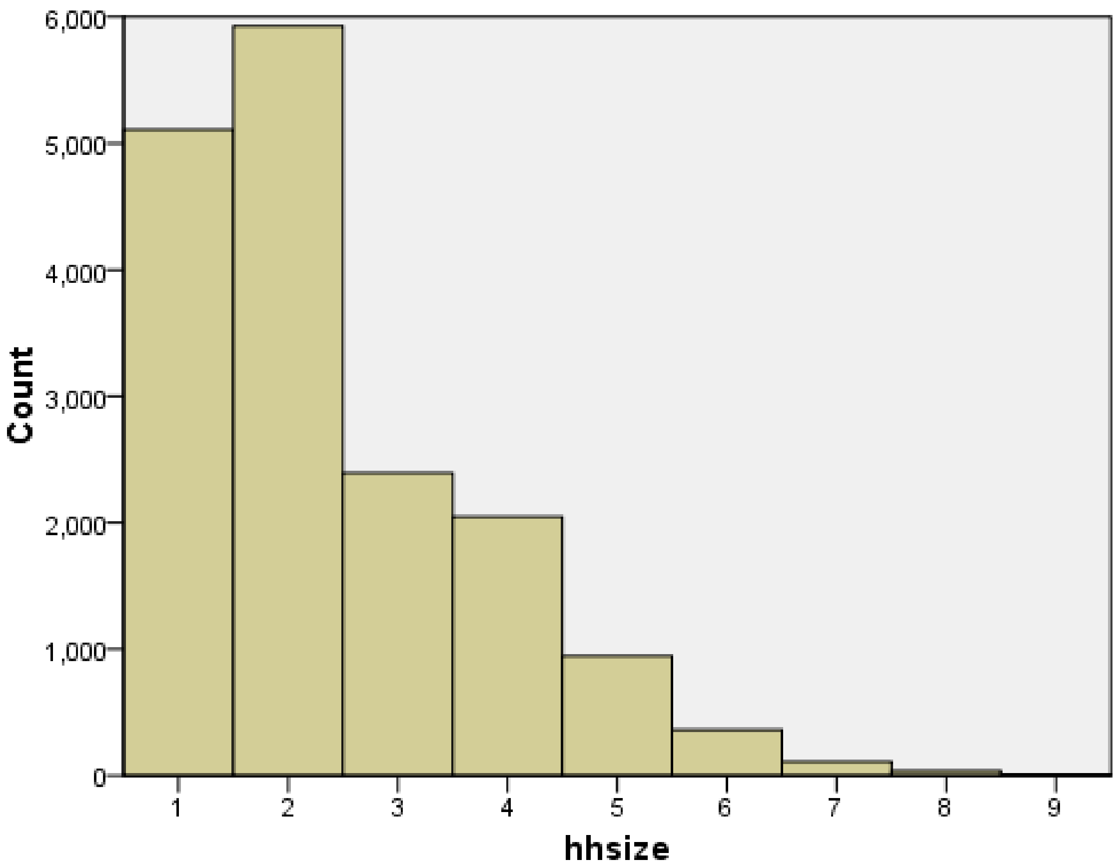

Figure 5.3 Distribution of household size

Table 5.3 Household size statistics

Household size	Counts	Percent	Cumulative Percent
1	5108	30.2	30.2
2	5929	35.0	65.2
3	2393	14.1	79.3
4	2045	12.1	91.4
5	946	5.6	96.9
6	362	2.1	99.1
7	109	.6	99.7
8	37	.2	99.9
9	10	.1	100.0
Total	16939	100.0	

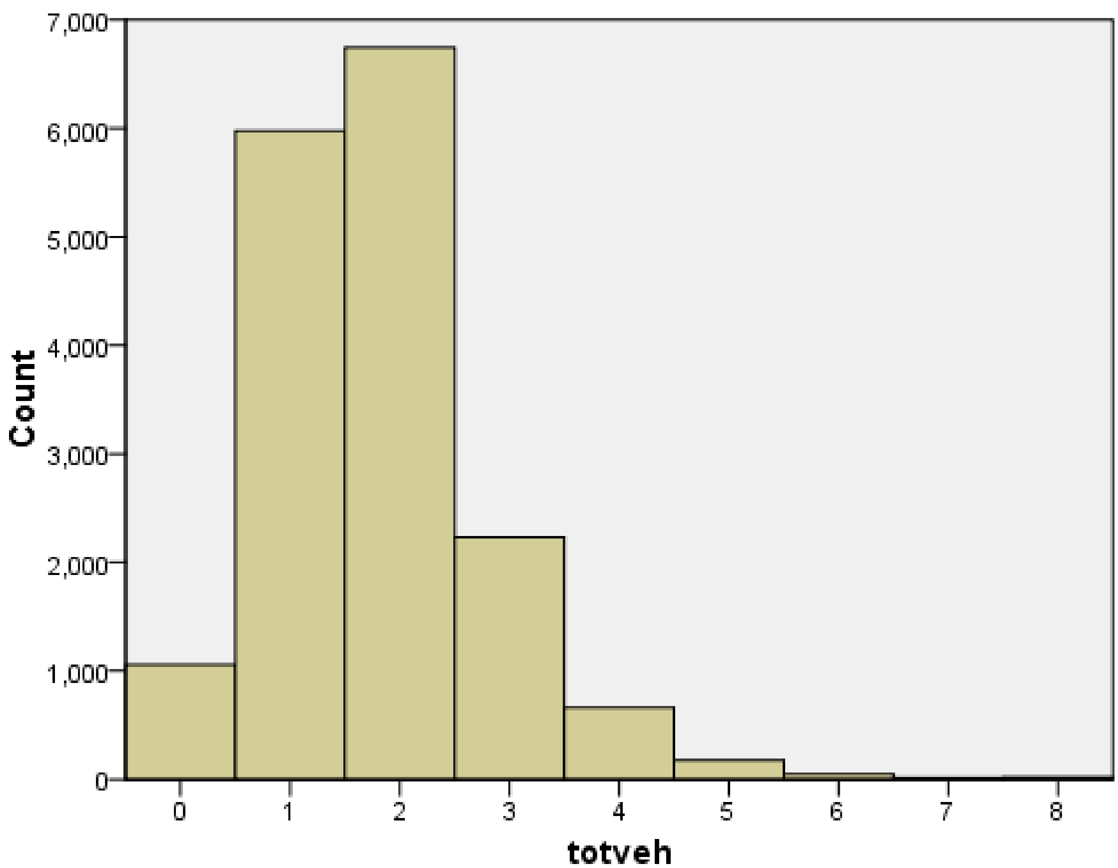

Figure 5.4 Distribution of number of vehicles of every household

Table 5.4 Number of vehicles statistics

Number of vehicles	Counts	Percent	Cumulative Percent
0	1059	6.3	6.3
1	5977	35.3	41.5
2	6745	39.8	81.4
3	2232	13.2	94.5
4	663	3.9	98.4
5	177	1.0	99.5
6	49	.3	99.8
7	16	.1	99.9
8	21	.1	100.0
Total	16939	100.0	

In the survey data, there is no direct field for activity types. However, there is an indication of primary trip purpose that we can use as activity types, as shown in Table 5.5.

Table 5.5 Primary trip purpose with statistics

Reference ID	Primary trip purpose	Counts	Percent
1	Change mode of transportation	2361	1.2
2	Pick up someone or get picked up	6240	3.3
3	Drop off someone or get dropped off	8072	4.2
4	ATM, buy gas, quick stop for coffee, newspaper, etc.	3005	1.6
5	Shopping	14084	7.4
6	Banking, post office, pay bills	3305	1.7
7	Work (include regular scheduled volunteer work)	14815	7.8
8	Work-related (sales call, meeting, errand, etc.)	5114	2.7
9	School (attending classes)	5836	3.1
10	Other school activities (sports, extra-curricular)	615	.3
11	Childcare, daycare, after school care	369	.2
12	Eat meal (restaurant, drive through, take out)	7524	4.0
13	Medical	2268	1.2
14	Fitness activity (playing sports, gym, bike	2426	1.3

	ride)		
15	Recreational (vacation, camping, etc.)	1331	.7
16	Entertainment (watching sports, movies, dance, bar, etc.)	2652	1.4
17	Visit friends/relatives	5448	2.9
18	Community meetings, political/civic event, public hearing	495	.3
19	Occasional volunteer work	381	.2
20	Church, temple, religious meeting	1493	.8
21	With another person at their activity out of home	2576	1.4
22	Other personal (specify)	6291	3.3
23	Working at home (related to main or second job)	691	.4
24	Other at home activities	91955	48.4
97	Other activity	444	.2
99	DK/RF (Don't know or refuse to answer)	378	.2
	Total	190169	100.0

We select shopping, and work activities as our main focus of interest in our research. We consider work activities as mandatory activities while shopping activities are voluntary activities. The majority of travel modes in the data set are 'Drove' and 'Passenger in car/truck/van' (see Table 5.6). There are 23.9% of trips that did not report what mode was used in the survey. For purposes of demonstration, we select data that reported using mode 'Drove' and 'Passenger in car/truck/van'.

Table 5.6 Mode of trip

Travel modes		Counts	Percent	Valid Percent	Cumulative Percent
1	Walk	11258	5.9	7.8	7.8
2	Bicycle	838	.4	.6	8.4
3	Drove	93489	49.2	64.6	72.9
4	Passenger in car/truck/van	34344	18.1	23.7	96.6
5	Local bus or community bus	1883	1.0	1.3	97.9
6	Express bus	76	.0	.1	98.0

7	Metro Blue Line	86	.0	.1	98.0
8	Metro Green Line	17	.0	.0	98.1
9	Metro Red Line	98	.1	.1	98.1
10	Commuter Rail (Metrolink, Amtrak)	98	.1	.1	98.2
11	Dial-A-Ride/Paratransit	33	.0	.0	98.2
12	School Bus	1511	.8	1.0	99.3
13	Greyhound Bus	14	.0	.0	99.3
14	Taxi/Shuttle Bus/Limousine	257	.1	.2	99.4
15	Motorcycle/Moped	71	.0	.0	99.5
97	Other	541	.3	.4	99.9
99	DK/RF	188	.1	.1	100.0
Total		144802	76.1	100.0	
No value		45367	23.9		
Total records		190169	100.0		

Because some people report performing the same activity multiple times in one day — activities performed multiple times are too complicated for analysis, so we filter out the data and keep only those who record the same activity only one time during the day. (These people can do many activities in a day, but each activity can be performed only one time.) We further subcategorize some activities with respect to the time-of-day. For example, ‘Work’ activities can be divided into ‘morning work’, ‘afternoon work’, ‘evening work’, and ‘eat meal’ can be divided into ‘breakfast’, ‘lunch’, ‘dinner’ , etc., depending on the range of time-of-day. For simplicity, we only consider data that record only one occurrence of any particular activity throughout the entire day and filter out data records containing the same type of activity multiple times. The following figures and results are generated by Matlab. There are 590 individuals who reported one shopping activity during the day and 3696 individuals who reported one work activity in the survey’s day using mode ‘Drove’ and ‘Passenger in car/truck/van’. These individuals are drawn from single person households in order to negate any effects pertaining to household interaction. Histograms of arrival time for shopping activities (trip purpose= 5), work activities (trip purpose=7) and their arrival time of return home are shown in Figure 5.5. Each band width is 30 minutes in the figure. From these figures, we can see that each activity has a peak arrival time. Because we are using a triangular linear function, a perfect data set should have a continuous increase before the peak arrival time and a continuous fall after the peak arrival time. We use 30-minute intervals as the time interval for the arrival time histogram, principally because we find that 30-minute interval has fewer missing representations. The missing drops between time intervals may be caused by people reporting rounded up arrival times forcing fewer representations in finer time intervals. We can see that the work activity has a clear peak arrival time compared to shopping activities. Also, work activities are more concentrated with respect to arrival time than to their return home arrival times. Figure 5.6 shows the activity duration histogram for shopping and work activities. Each band width is 5 minutes. The duration of shopping activity is very concentrated to less than 100 minutes, while the duration of work activity has a wider range with longer duration than shopping activity. Figure 5.7 shows the leave home times at the start of day for every person in the survey (except for those who never leave home for the whole day). Figure 5.8 shows the arrival time at the end of day of every person in the survey (except for those who never leave home for the whole day). These data include all activity purposes, all travel modes and people performing one or multiple activities during the day. Each band width is 30 minutes. A continuous increase before the peak arrival time and a continuous fall after the peak arrival time is clearly observed. Statistical information regarding the arrival times and activity durations are needed in our analysis.

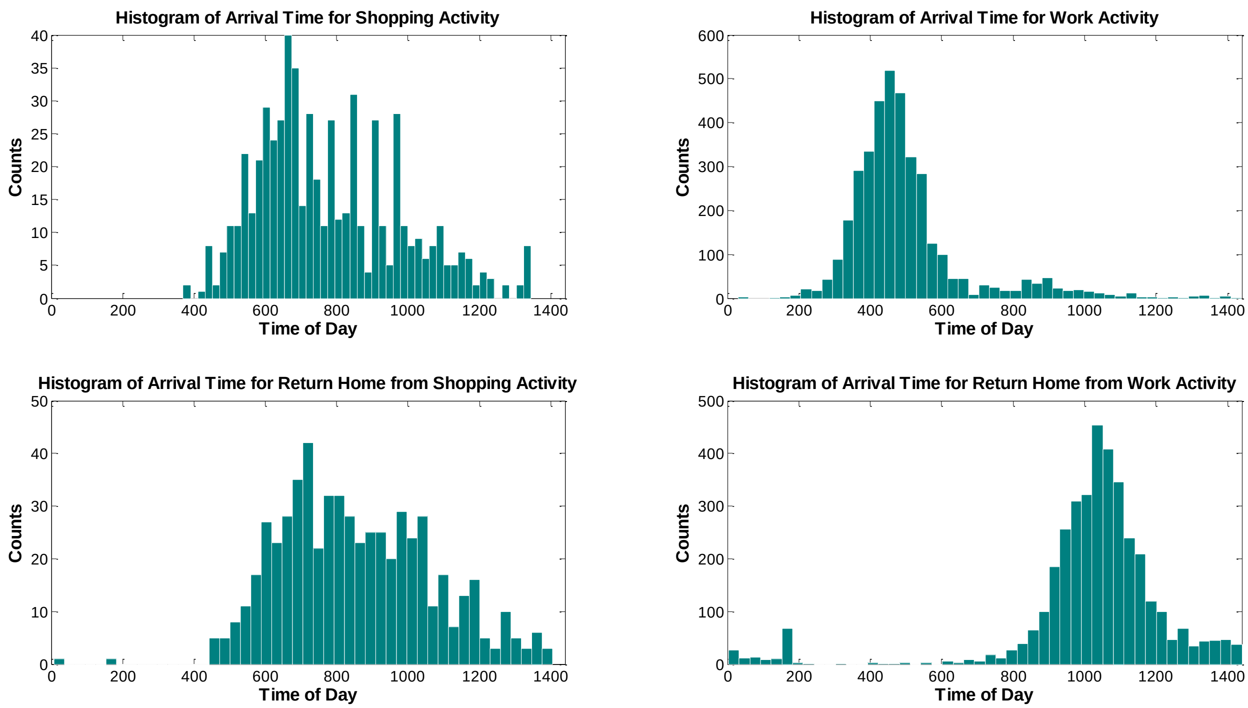

Figure 5.5 Histogram of arrival time on shopping (return home) and work (return home) activities (divide 24 hours into 1440 minutes)

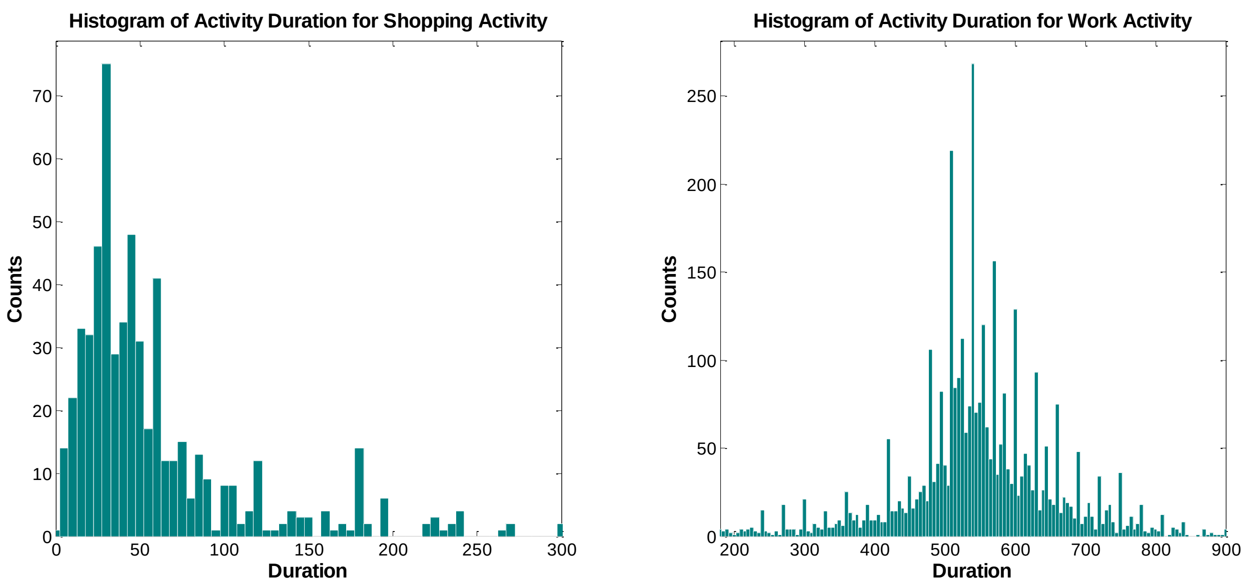

Figure 5.6 Histogram of activity duration for shopping and work activities

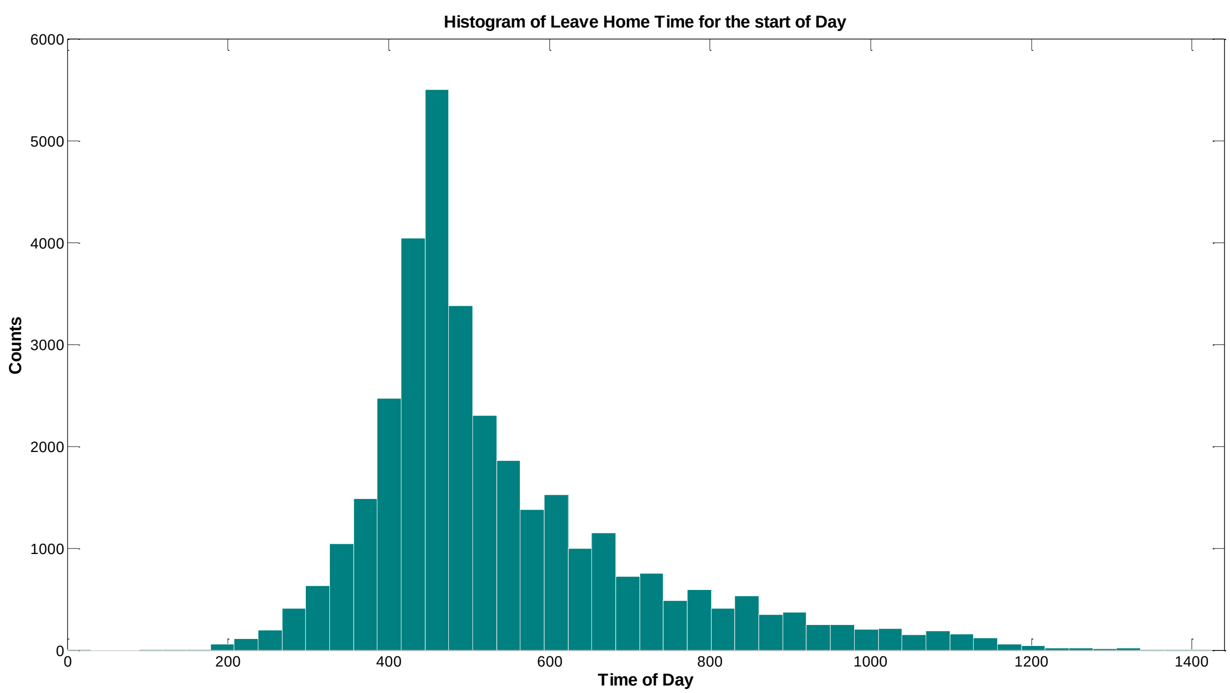

Figure 5.7 Histogram of departure home time at the beginning of day (divide 24 hours into 1440 minutes)

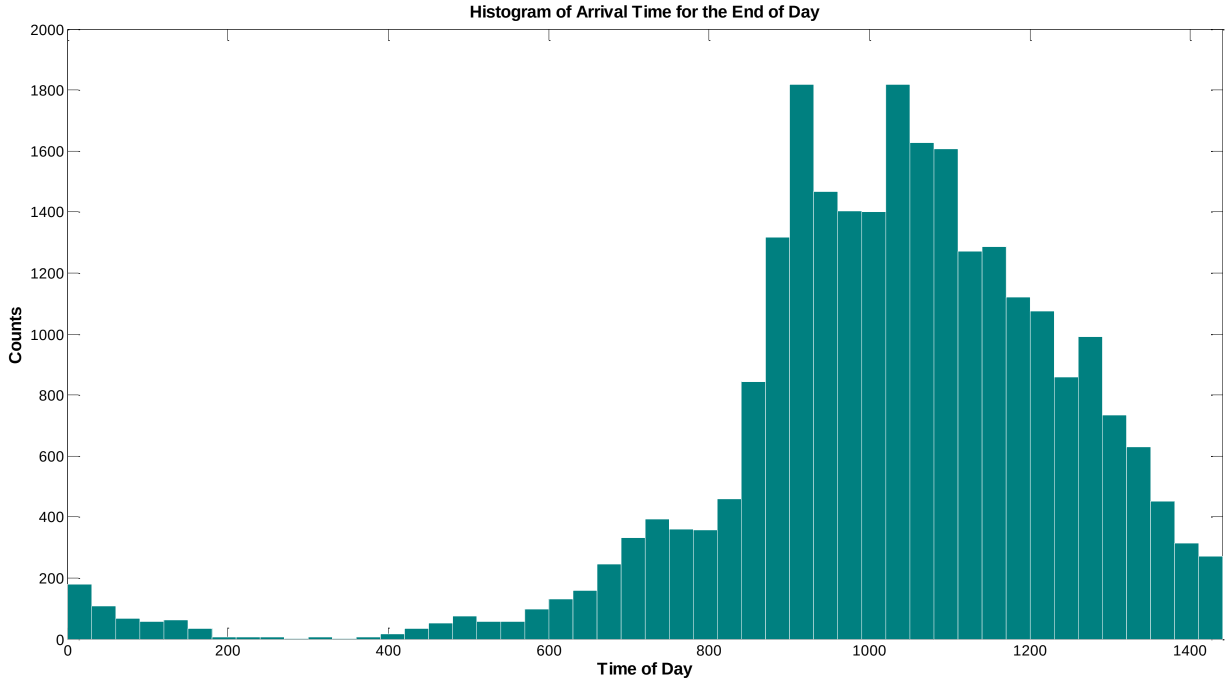

Figure 5.8 Histogram of arrive home time at the end of day (divide 24 hours into 1440 minutes)

Statistical inferences obtained from survey data

In this section, we will use linear regression to obtain parameters and coefficients for each activity, i.e., $a_i^\alpha, b_i^\alpha, \mu_i^\alpha, K_{ie}^\alpha, K_{il}^\alpha, U_{i\_min}^\alpha, U_{i\_max}^\alpha, s_{i\_min}^\alpha, s_{i\_max}^\alpha, K_{is}^\alpha,$ needed for TUHAPP (UHAPP). Figure 5.9 shows the data processing procedures for obtaining TUHAPP (UHAPP) parameters and coefficients. Based on the data we have shown in Figure 5.5, Figure 5.6, Figure 5.7 and Figure 5.8, we will infer the distribution to be triangular linear demand function. In the inferences, we select individuals who perform only one out-of-home activity throughout the day. Our assumption here is that, because there presumably are no other activity scheduling constraints there will be fewer constraints on activity arrival times and activity duration, and people will choose arrival times and activity durations closer to their maximum utility values. We apply a ‘one person one vote’ policy to evaluate the “demand” for arrival time preference for each 30-minute slot throughout the day. To derive a better linear demand curve we eliminate the time slots that have less than 15% of the representation of the whole data. We also filter out the spike from the early morning arrival which is shown in the histogram of “arrive home from work activity” in Figure 5.5. Figure 5.10 shows the arrival time utility function from linear regression for shopping, return home from shopping, work and return home from work activates. Figure 5.11 and Figure 5.12 show the departure time and the arrival time utility functions obtained from linear regression for the start of the day and the end of day, respectively. Each departure or arrival utility function consists of two linear functions. The blue line before the peak departure (arrival) time has a continuous utility increase until the peak departure (arrival) time. Alternatively, the red line after the peak departure (arrival) time has a continuous utility decease until it reaches zero utility. Table 5.7 shows the linear demand curve parameters for these six activities. Table 5.8 shows the linear demand curve statistics of each activity. Although the sample size of each activity is relatively small (due to 30-minute interval and data filtering), we still have a good confidence statistic on this linear demand function. Unlike our examples on Chapter 3 and Chapter 4, the linear demand curve is discontinuous and we have calculated the gap (utility drop after the peak arrival time) of the discontinuity. The utility drop of work arrival is relatively large compared to shopping activity arrival times. This may help to explain why people tend to concentrate the arrival time and put more utility before the peak hour than after the peak hour. The assumption of using triangular linear demand curve may not be accurate, but it does simplify our analysis on using TUHAPP (UHAPP), which is a linear optimization problem.

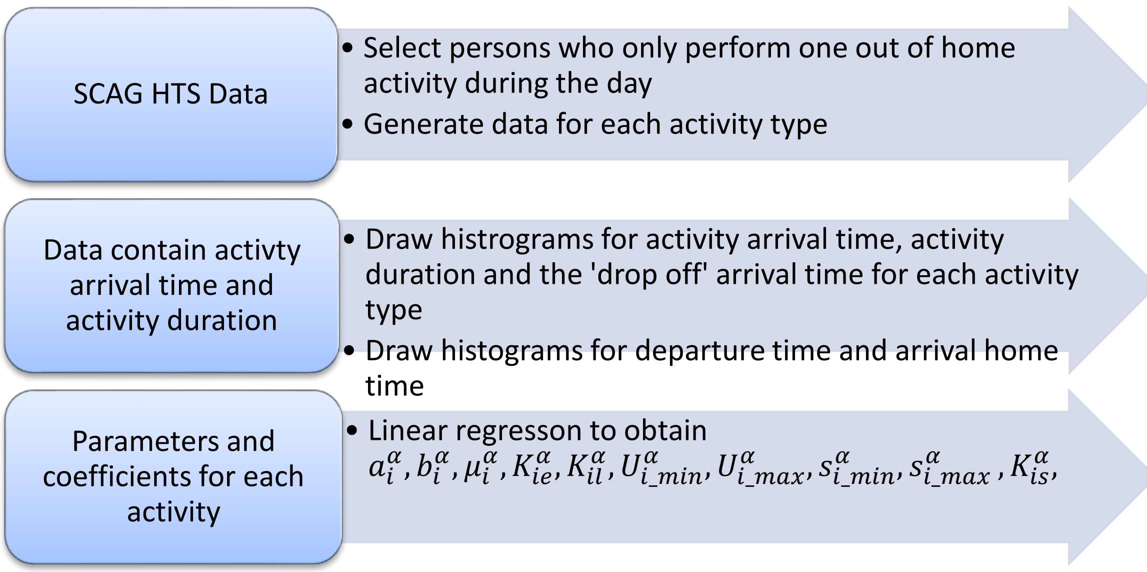

Figure 5.9 Procedures of obtaining UHAPP (TUHAPP) parameters of each activity

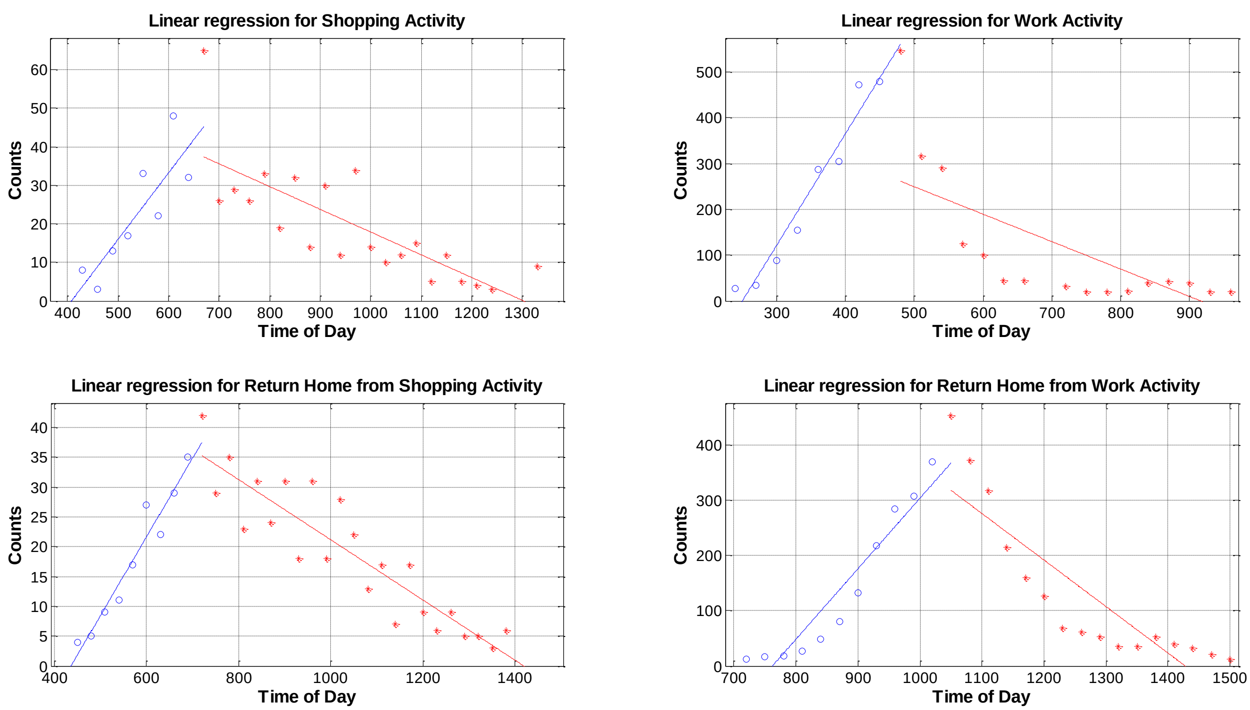

Figure 5.10 Arrival time utility function of shopping, return home from shopping, work and return home from work activities, respectively (divide 24 hours into 1440 minutes)

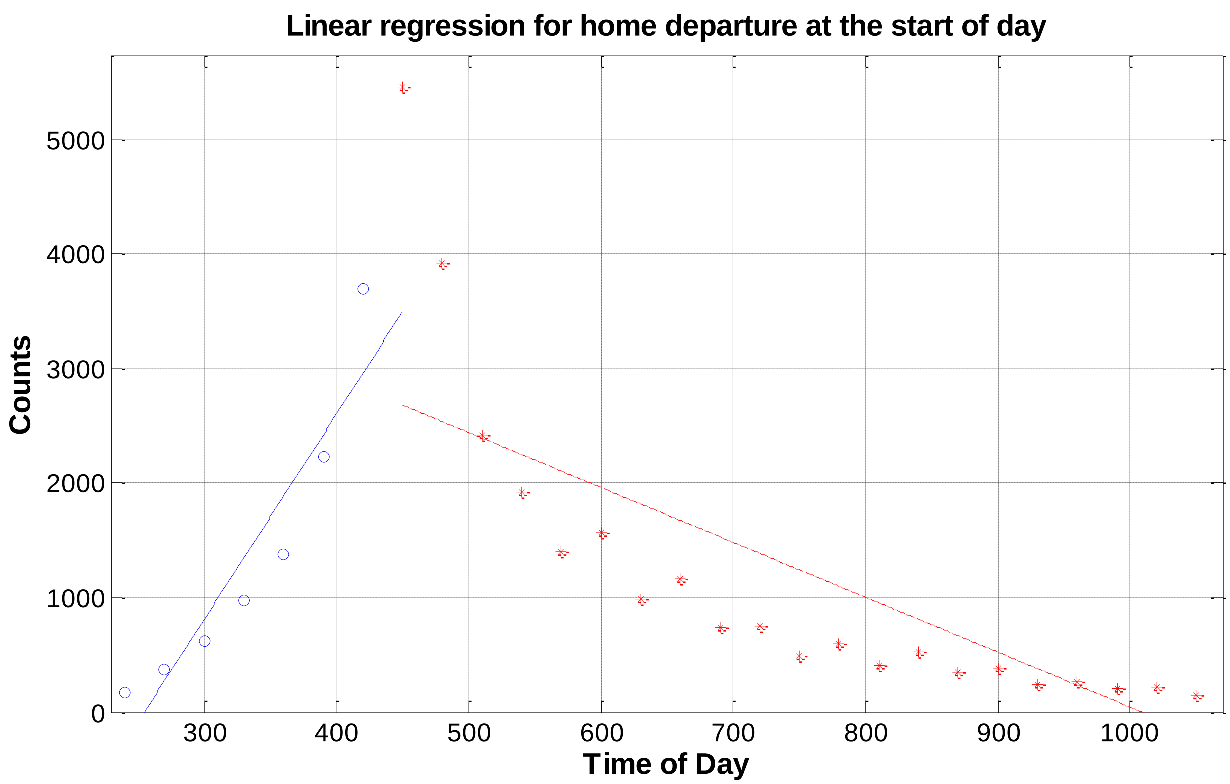

Figure 5.11 Departure time utility function of leaving home at the start of day (divide 24 hours into 1440 minutes)

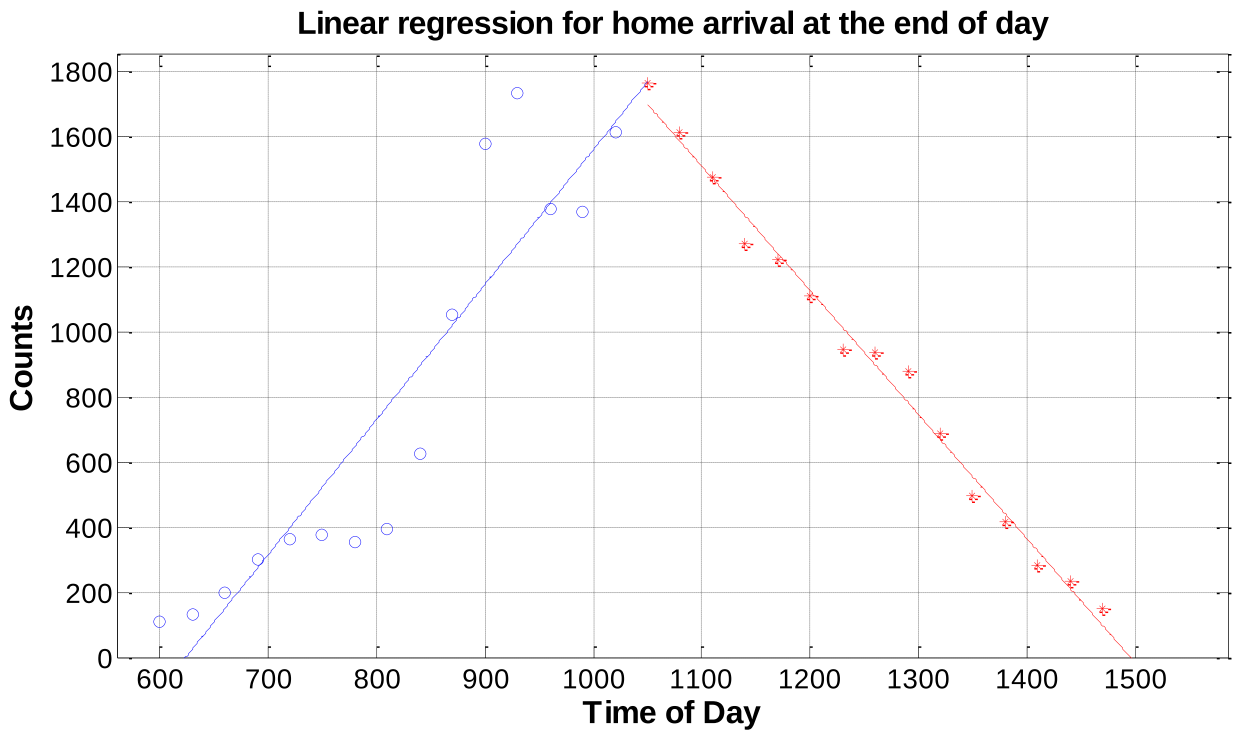

Figure 5.12 Arrival time utility function of arrive home at the end of day (divide 24 hours into 1440 minutes)

Table 5.7 Linear demand curve parameters

Activity type	a_i	μ_i	b_i	K_{ie}	K_{il}	Gap
Shopping	408	670	1302	0.173	-0.0591	7.9813
Work	250	480	916	2.4405	-0.5995	299.2445
Return home from shopping	436	720	1419	0.1322	-0.0506	2.1630
Return home from work	762	1050	1428	1.2764	-0.8419	48.3892
Depart home at the start of day	255	450	1009	17.9119	-4.795	817.4829
Arrive home at the end of day	624	1050	1496	4.1439	-3.8099	67.7345

Table 5.8 Linear demand curve statistics

Activity type	R^2	F_{test}	p value
Shopping (blue)	0.7253	15.8449	0.0073
Shopping (red)	0.5968	28.1190	4.0613×10^{-5}

Work (blue)	0.9542	125.0099	3.0549×10^{-5}
Work (red)	0.5224	17.5038	7.0194×10^{-4}
Return home from shopping (blue)	0.9422	114.0702	1.3841×10^{-5}
Return home from shopping (red)	0.8253	99.1902	2.0803×10^{-9}
Return home from work (blue)	0.9036	84.3559	7.2296×10^{-6}
Return home from work (red)	0.7545	43.0362	1.2696×10^{-5}
Depart home at the start of day (blue)	0.8691	33.2110	0.0022
Depart home at the start of day (red)	0.6104	34.4736	6.5827×10^{-6}
Arrive home at the end of day (blue)	0.8428	69.7226	1.395×10^{-6}
Arrive home at the end of day (red)	0.9902	1312.9	1.9176×10^{-14}

In order to run TUHAPP (UHAPP) using survey data, we also need to have a linear activity duration function. Figure 5.13 shows the linear utility duration function of shopping and work activities, respectively. Table 5.9 shows those linear parameters of utility duration function. We approximate the cumulative distribution function of the duration to obtain the linear utility duration function. Table 5.10 shows the linear statistics of these utility duration function. Because the duration of work activity is more scatter than the duration of shopping activities, the R^2 is not as significant as duration of shopping activity. We set up the minimum duration of shopping as 5 minutes and obtain the minimum duration utility as 0. We set up the minimum duration of work as 400 minutes and obtain the minimum duration utility as 0.

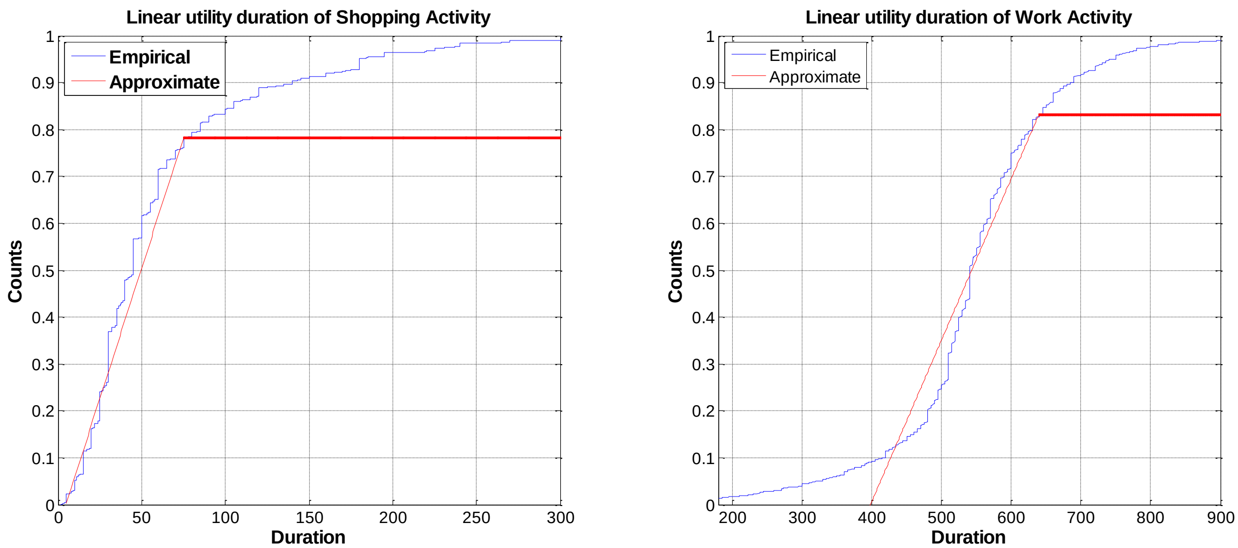

Figure 5.13 Utility of duration on shopping and work activity

Table 5.9 Utility function of shopping, and work duration

Activity (i)	$U^{\alpha}_{i\_min}$	$s^{\alpha}_{i\_min}$	$s^{\alpha}_{i\_max}$	K^{α}_{is}
Shopping	0	7	65	0.0111
Work	0	300	640	0.0034

Table 5.10 Linear utility duration function statistics

Activity (i)	R^2	F_{test}	p value
Shopping	0.9637	31.3876	0.7648
Work	0.8673	27.3845	2.174×10^{-2}

The objective function of TUHAPP

Based on the availability of data, we have the objective function of TUHAPP as follow

$$Max\ U = \sum_{\alpha\in\eta}\sum_{i\in D}\sum_{j\in N}\sum_{p\in P}\beta_{1i} f(T_i^\alpha) H_{ij}^{\alpha p} + \sum_{\alpha\in\eta}\sum_{i\in L^+}\sum_{j\in N}\sum_{p\in P}\beta_{2i} g(S_i^\alpha) H_{ij}^{\alpha p} - \beta_3 \sum_{v\in V}\sum_{i\in N}\sum_{j\in N}\sum_{p\in P} t_{ij}^{vp} X_{ij}^{vp} \qquad (5\text{-}1)$$

Because we do not have travel costs of each OD pair of nodes and the initial cost of using vehicles of out of home activities, we only consider three objectives in our forecasting model. $\sum_{\alpha\in\eta}\sum_{i\in D}\sum_{j\in N}\sum_{p\in P}\beta_{1i} f(T_i^\alpha) H_{ij}^{\alpha p}$ is the first objective of the TUHAPP forecasting model. This objective means arrival time gives certain amount of utility to each person and the sum of all activity arrival time utility of each person in the household weighted by β_{1i}. T_i^α is a continuous variable and $f(T_i^\alpha)$ is a discontinuous piecewise linear function based on Figure 5.10 and Figure 5.12. These values $a_i^\alpha, b_i^\alpha, \mu_i^\alpha, K_{ie}^\alpha,\ K_{il}^\alpha$ will determine the shape of $f(T_i^\alpha)$. We have shown the process of getting $a_i^\alpha, b_i^\alpha, \mu_i^\alpha, K_{ie}^\alpha,\ K_{il}^\alpha$ in last section. The value of T_i^α will determine the value of $\sum_{i\in D}\sum_{\alpha\in\eta} f(T_i^\alpha)$. If there is no constraint on T_i^α, T_i^α will be equal to μ_i^α. β_{1i} is the relative weight of $\sum_{\alpha\in\eta}\sum_{i\in D}\sum_{j\in N}\sum_{p\in P} f(T_i^\alpha) H_{ij}^{\alpha p}$ compared to other objectives.

$\sum_{\alpha\in\eta}\sum_{i\in L^+}\sum_{j\in N}\sum_{p\in P}\beta_{2i} g(S_i^\alpha) H_{ij}^{\alpha p}$ is the second objective of the model. It means the duration of activities will give certain amount of utility to each person. S_i^α is a continuous variable and $g(S_i^\alpha)$ is a piecewise linear function based on Figure 5.13. The values $U_{i\_min}^\alpha, U_{i\_max}^\alpha, s_{i\_min}^\alpha, s_{i\_max}^\alpha, K_{is}^\alpha$ will determine the shape of $g(S_i^\alpha)$ and we have shown the methodology of obtaining these values in 0. The value of S_i^α will determine the value of $\sum_{i\in L^+}\sum_{\alpha\in\eta} g(S_i^\alpha)$. If there is no constraint on S_i^α, S_i^α will be greater than or equal to $s_{i\_max}^\alpha$, and $\sum_{i\in L^+}\sum_{\alpha\in\eta} g(S_i^\alpha)$ will be equal to

$\sum_{i \in L^+} \sum_{\alpha \in \eta} U_{i\_max}^{\alpha}$. β_{2i} is the relative weight of $\sum_{\alpha \in \eta} \sum_{i \in L^+} \sum_{j \in N} \sum_{p \in P} g(S_i^{\alpha}) H_{ij}^{\alpha p}$ compared to other objectives. $-\beta_3 \sum_{v \in V} \sum_{p \in P} \sum_{i \in N} \sum_{j \in N} t_{ij}^{vp} X_{ij}^{vp}$ is the third objective of the model. It is negative because we assume travel between activities and home has only a cost. $t_{ij}^{vp} X_{ij}^{vp}$ is not a continuous function because X_{ij}^{vp} is an integer variable and it is equal to either 0 or 1. t_{ij}^{vp} is in general a step function based on time periods and it is also not a continuous function. β_3 is the relative weight of $\sum_{v \in V} \sum_{p \in P} \sum_{i \in N} \sum_{j \in N} t_{ij}^{vp} X_{ij}^{vp}$ compared to other objectives. We assume β_3 is uniform distributed for every activity and every person. If β_{1i} and β_{2i} are 0, then TUHAPP is just a shortest path problem and β_3 becomes irrelevant because $-\beta_3 \sum_{v \in V} \sum_{p \in P} \sum_{i \in N} \sum_{j \in N} t_{ij}^{vp} X_{ij}^{vp}$ is the only objective. The optimal solution of the shortest path problem is the optimal solution of TUHAPP. If β_2 is 0 but β_1 and β_3 are not 0, then the problem becomes to be a shortest path problem with resource constraints. The solution for the shortest path problem may not be the optimal solution for TUHAPP anymore. If β_{1i} is very small, but β_3 is very big, then the optimal solution of TUHAPP should be very close to the solution of a shortest path problem. Vice versa, if β_1 is very big, but β_3 is very small (or even 0), then TUHAPP becomes closer to a linear optimization problem. Based on the availability of data, we have $T_i^{\alpha}, S_i^{\alpha}, t_{ij}^{vp} X_{ij}^{vp}, H_{ij}^{\alpha p}$ as we have shown in last section. Because we assume those three objectives are the main forces driving the solution, what we observe from the data should also reflect this assumption.

Calibration of weight distribution

Even though we have relative utility functions of activity arrival and activity duration, we still need to have the distributed weights for each component of the objective as explained in the last section. With the input we have in Table 5.7, Table 5.9 and the survey data, we can start to calibrate β_{1i}, β_{2i} and β_3. However, we note that for a given observation, β_{1i}, β_{2i} and β_3 are not unique, which means many combination of β_{1i}, β_{2i} and β_3 can give the same solution. But, because utility is an abstract concept, a utility of any quantity will have no meaning, only when there is a relative difference then the utility will generate a preference alternative that the consumer will choose. Thus, we only care about the relative differences in each distributed weight, not the absolute value of the betas and the absolute value of optimal objective value. We use the recorded travel times from the survey rather than network times so as not to introduce more errors to the calibration process. There are many reasons behind the difference of reported travel times comparing to the model output travel times, such as model forecasting inaccuracy (Parthasarathi & Levinson, 2010), the shortest path is not chosen (Zhu & Levinson, 2010), and the time perception of different people (Grondin, 2010). For the purpose of calibration, we will use the reported travel time and use the model network travel time for validation purpose. Because the travel survey has only one reported travel time for each trip the person makes, we assume the reported travel time is the same for every time period. We drop the α index because our example application involves a one-person household. The following example shows calibrating a single household with one work and one shopping activity. The objective function of TUHAPP (because travel time is the same for every period, this is the same as calibrating UHAPP) we try to calibrate is

$$
\begin{aligned}
Max\ U = {} & \beta_0 \sum_{p\in P}\sum_{i\in L^+} f(T_0)H_{0,i}^p + \beta_{work\_arrival}\sum_{j\in N}\sum_{p\in P} f(T_{work})H_{work,j}^p \\
& + \beta_{shopping\_arrival}\sum_{j\in N}\sum_{p\in P} f(T_{shopping})H_{shopping,j}^p \\
& + \beta_{return}\sum_{p\in P}\sum_{i\in L^-}\sum_{j\in N} f(T_i)H_{ij}^p + \beta_{2n+1}\sum_{p\in P}\sum_{i\in L^-} f(T_{2n+1})H_{i,2n+1}^p \\
& + \beta_{work\_duration}\sum_{j\in N}\sum_{p\in P} g(S_{work})H_{work,j}^p \\
& + \beta_{shopping\_duration}\sum_{j\in N}\sum_{p\in P} g(S_{shopping})H_{shopping,j}^p \\
& - \beta_{traveltime}\sum_{p\in P}\sum_{i\in N}\sum_{j\in N} t_{ij}^p X_{ij}^p
\end{aligned}
\tag{5-2}
$$

where $\beta_0 \sum_{p\in P}\sum_{i\in L^+} f(T_0)H_{0,i}^p$ is the utility of departure time at the start of day.

$\beta_{shopping\_arrival}\sum_{j\in N}\sum_{p\in P} f(T_{shopping})H_{shopping,j}^p$ and

$\beta_{work\_arrival}\sum_{j\in N}\sum_{p\in P} f(T_{work})H_{work,j}^p$ are the utility of arrival time of the activity.

$\beta_{return}\sum_{p\in P}\sum_{i\in L^-}\sum_{j\in N} f(T_i)H_{ij}^p$ is the utility of drop off arrival time of the activity.

$\beta_{2n+1}\sum_{p\in P}\sum_{i\in L^-} f(T_{2n+1})H_{i,2n+1}^p$ is the utility of arrival time at the end of day.

$\beta_{shopping\_duration}\sum_{j\in N}\sum_{p\in P} g(S_{shopping})H_{shopping,j}^p$ and

$\beta_{work\_duration}\sum_{j\in N}\sum_{p\in P} g(S_{work})H_{work,j}^p$ is the utility of activity duration.

$\beta_{traveltime}\sum_{p\in P}\sum_{i\in N}\sum_{j\in N} t_{ij}^p X_{ij}^p$ is the disutility of the total travel time during the day. We separate the pickup and drop-off objectives because this will allow different weights on arrival at activities and arrival home. Compared to previous research (Chow & Recker, Inverse optimization with endogenous arrival time constraints to calibrate the household activity pattern problem, 2012) on calibrating β_i, we calibrate the weight of arrival time utility of each activity location where each person has visited during the day instead of treating them equal and calibrating the sum of the objectives. Our objective is to find a set of betas that can give optimal solutions in the sense that they are closest to the observed data. Because each household is different, we will focus our attention on calibrating betas for each household. The objective of the calibration is

$$Min \sum_i L_i = \sum_i (|T_i^{TUHAPP} - T_i^{Obs}|) + \sum_i (|S_i^{TUHAPP} - S_i^{Obs}|) \tag{5-3}$$

where $\sum_i L_i$ is the Manhattan distance of the sum of observation values and predicted values by TUHAPP. We follow the same criteria from Chow (Chow & Recker, Inverse optimization with endogenous arrival time constraints to calibrate the household activity pattern problem, 2012) to choose L_1norm as our perturbation distance. T_i^{TUHAPP} is the predicted activity arrival time from TUHAPP of each observation i. T_i^{Obs} is the reported activity arrival time from survey data of each observation i. S_i^{TUHAPP} is the predicted activity duration from TUHAPP of each observation i. S_i^{Obs} is the reported activity duration from survey data of each observation i. The optimal solution will be the β combination that can predict a result that is the closest to the observation. Because the above objective function is not linear, we need to transfer this function to a linear function by adding the following constraints.

$$L_i \geq T_i^{TUHAPP} - T_i^{Obs} + S_i^{TUHAPP} - S_i^{Obs} \tag{5-4}$$

$$L_i \geq -T_i^{TUHAPP} + T_i^{Obs} + S_i^{TUHAPP} - S_i^{Obs} \tag{5-5}$$

$$L_i \geq T_i^{TUHAPP} - T_i^{Obs} - S_i^{TUHAPP} + S_i^{Obs} \tag{5-6}$$

$$L_i \geq -T_i^{TUHAPP} + T_i^{Obs} - S_i^{TUHAPP} + S_i^{Obs} \tag{5-7}$$

For each household, we will perform the calibration process as the following steps:

1. Initiate $\beta_0 = \beta_{work\_arrival} = \beta_{shopping\_arrival} = \beta_{return} = \beta_{2n+1} = \beta_{work\_duration} = \beta_{shopping\_duration} = \beta_{traveltime} = 1$.
2. Run TUHAPP to get a predicted activity patterns of T_i^α and S_i^α.
3. Calculate the edit distance (multidimensional scaling) between the predicted and actual, L_i.
4. Go back to step 2 with a new set of betas.
5. Keep doing this until a minimum (or acceptable) edit distance is reached.

Here we assume that each household is independent of others—one combination of betas may work perfectly for one particular household, but it may give no information on other households. In economics, utility is a representation of preferences over some set of goods and services. There are two types of utilities, cardinal utilities and ordinal utilities. Because we choose cardinal utilities in the objective function of UHAPP and TUHAPP, we need to be careful in explaining the absolute value of the optimal objective value. Usually the absolute optimal objective value gives no meaning to the consumer because utility is an abstract concept. Only the relative differences in the distributed weights can give us some idea on how much the tradeoff among the utility components the consumer considers is important. Each household has a unique utility which is an abstract figure we try to quantify. For example, if household A puts more weight on shopping duration, it may give a higher utility for household A, so we may have an optimal objective value 100 for this household, but this means absolutely nothing to household B even if household B only has an optimal objective value 20. Household B may still think their objective is optimal given the fact that they may put more weight on arrival on the peak hour at work. We cannot use the distributed weights from household A to household B directly because we assume each household is independent in terms of choosing activity arrival time and activity duration.

Thus, using a set of betas to represent inhomogeneous households will have no credibility to the analyst. By calibrating betas for each household, we will generate a matrix that contains betas for each household. Then by using population synthesis, which is a process of replicating identical households to generate a synthetic population, we can have a matrix of betas that represent the whole region population.

Let's choose one sample household to see how we can calibrate betas. We select a single household (ID 12023859) that performs two out-of-home activities, namely: one work and one shopping activity. Table 5.11 shows the travel diary of this selected household. This individual leaves home at 8:00 (480), and arrives at work at 8:17 (497) spends 591 minutes at work then arrive to shopping at 18:38 (1118) and spends 18 minutes there. We use the travel time data from the travel diary and symmetrically fill in the unknown travel times as shown in Table 5.12.

Table 5.11 Sample household ID 12023859 travel diary data

Activities	T_i	t_{ij}	S_i
0	480	17	-
1	497	30	591
2	1118	28	18
3	1164	-	-

Table 5.12 Travel times for each node to node pair in every time period (minutes) household ID 12023859

NODES	0	1	2	3	4	5
0	0	17	28	0	0	0
1	17	0	30	17	17	17
2	28	30	0	28	28	28
3	0	17	28	0	0	0
4	0	17	28	0	0	0

5	0	17	28	0	0	0

Table 5.13 Different beta scenarios on household ID 12023859

Betas	Base case	Case 1	Case 2
$\boldsymbol{\beta_0}$	1	1	1
$\boldsymbol{\beta_{work\_arrival}}$	1	1	20
$\boldsymbol{\beta_{shopping\_arrival}}$	1	1	1
$\boldsymbol{\beta_{return}}$	1	1	1
$\boldsymbol{\beta_{2n+1}}$	1	1	1
$\boldsymbol{\beta_{work\_duration}}$	1	18	1500
$\boldsymbol{\beta_{shopping\_duration}}$	1	1	200
$\boldsymbol{\beta_{traveltime}}$	1	1	1

We first run TUHAPP in base case scenario where all betas are 1. We have a solution as shown in Table 5.14. Our objective is to

$$Min \sum_i L_i = \sum_i (|T_i^{UHAPP} - T_i^{Obs}|) + \sum_i (|S_i^{UHAPP} - S_i^{Obs}|) \tag{5-3}$$

Let's see how TUHAPP solution comparing to the observation. $\sum_i L_i = |450 - 480| + |467 - 497| + |797 - 1118| + |1050 - 1164| * 3 + |300 - 591| + |225 - 18| = 30 + 30 + 321 + 114 * 3 + 291 + 207 = 1221$. It seems the base case scenario has a lot of room to narrow this gap, especially given the fact that work duration is neither the minimum nor the maximum and shopping duration is much greater than observation. It seems that this person spends more time on work so he arrives to shopping later than what TUHAPP model has predicted, also the solution has a longer duration for shopping, so let's increase $\beta_{work\_duration}$ to generate another solution. We increase $\beta_{work\_duration}$ by 1 increments until $\beta_{work\_duration} = 18$ then we have a new set of solutions as shown in Table 5.14. Let's see how this solution compares to the observation. $\sum_i L_i = |450 - 480| + |467 - 497| + |957 - 1118| + |1050 - 1164| * 3 + |460 - 591| + |65 - 18| = 30 + 30 + 161 + 114 * 3 + 131 + 65 = 741 < 1221$. It seems case 1 fits this survey data better than base case scenario, but it may still have room to narrow the gap. It seems this individual prefers leaving home late at the beginning of the day, which will push all of the arrival times on all activities later than the social norm. After a few more trials and errors, we have case 2 betas and solutions in Table 5.14. Although case 2 betas are likely not the unique combination of betas (because we arbitrarily just stop on the trial) that minimize the error between predicted and actual, it has the best fit to the observation thus far (this is a heuristic process so far). But as we mentioned, we are only interested on the relative difference of each distributed weight. Let's see how this solution compares to the observation. $\sum_i L_i = |463 - 480| + |480 - 497| + |1150 - 1118| + |1185 - 1164| * 3 + |640 - 591| + |7 - 18| = 17 + 17 + 32 + 21 * 3 + 49 + 11 = 189 < 741$. We conclude that case 2 provides the best beta combination to generate the closest solution compared to survey data. Of course, other beta combinations may also generate the same solution, but our purpose is not to list all the possible betas here; nor is it to develop an appropriate heuristic to search for 'optimal' betas.

Table 5.14 TUHAPP solutions on each case scenario at household ID 12023859

	Observation		**Base case**		**Case 1**		**Case 2**	
Activities	T_i	S_i	T_i	S_i	T_i	S_i	T_i	S_i
0	480	-	450	-	450	-	463	-
1	497	591	467	300	467	460	480	640
2	1118	18	797	225	957	65	1150	7
3	1164	-	1050	-	1050	-	1185	-
4	1164	-	1050	-	1050	-	1185	-
5	1164	-	1050	-	1050	-	1185	-
Difference	0		1221		741		189	

Let's choose another single person household (ID 12048694) and calibrate betas. According to the travel diary (Table 5.15), this person leaves home at 8:30 (510) travel 45 minutes to work at 9:15 (555), and spends 495 minutes at work. Then this person travels 60 minutes and arrives at shopping activity at 18:30 (1110) and spends 20 minutes there. After that this person travels 10 minutes and gets home at 19:00 (1140). We use the travel time data from the travel diary and symmetrically fill in the unknown travel times as shown in Table 5.16.

Table 5.15 Sample household ID 12048694 travel diary data

Activities	T_i	t_{ij}	S_i
0	510	45	-
1	555	60	495
2	1110	10	20
3	1140	-	-

Table 5.16 Travel times for each node to node pair in every time period (minutes) household ID 12048694

NODES	0	1	2	3	4	5
0	0	45	10	0	0	0
1	45	0	60	45	45	45
2	10	60	0	10	10	10
3	0	45	10	0	0	0
4	0	45	10	0	0	0
5	0	45	10	0	0	0

Table 5.17 Different beta scenarios on household ID 12048694

Betas	Base case	Case 1	Case 2	Case 3
$\boldsymbol{\beta_0}$	1	1	1	1
$\boldsymbol{\beta_{work\_arrival}}$	1	1	10	20
$\boldsymbol{\beta_{shopping\_arrival}}$	1	1	1	1

$\boldsymbol{\beta_{return}}$	1	1	1	1
$\boldsymbol{\beta_{2n+1}}$	1	1	1	1
$\boldsymbol{\beta_{work\_duration}}$	1	18	200	1500
$\boldsymbol{\beta_{shopping\_duration}}$	1	1	8	200
$\boldsymbol{\beta_{traveltime}}$	1	1	1	1

We first run TUHAPP in base case scenario where all betas are 1. We have solutions showing in Table 5.18. Let's see how base case betas TUHAPP solution comparing to the observation. $\sum_i L_i = |450 - 510| + |495 - 555| + |855 - 1110| + |1050 - 1140| * 3 + |300 - 495| + |185 - 20| = 60 + 60 + 255 + 90 * 3 + 195 + 165 = 1005$. It seems the base case scenario fits the observation better than our last example. We also increase $\beta_{work\_duration}$ by 1 increments until $\beta_{work\_duration} = 18$ to have a new set of solutions as shown in Table 5.18. This illustrates that the relative difference on betas are not tied to the data but to the model itself which is TUHAPP (UHAPP) given the known utility on arrival time and utility on duration. Let's see how this solution compares to the observation. $\sum_i L_i = |450 - 510| + |495 - 555| + |975 - 1110| + |1050 - 1140| * 3 + |420 - 495| + |65 - 20| = 60 + 60 + 135 + 90 * 3 + 75 + 45 = 645$. It seems case 1 betas fit this reported household's travel diary better than does the base case scenario. Work duration and arrival time on shopping fit closer to observation. Base case betas and case 1 betas both fit better in household ID 12048694 than household ID 12023859. Because leave home time at the start of day and arrival time at the end of day are already at peak hours, which are 450 and 1050, we may move the work duration and shopping duration a little bit more to fit the observation better. We have case 2 scenario $\sum_i L_i = |450 - 510| + |495 - 555| + |1033 - 1110| + |1050 - 1140| * 3 + |478 - 495| + |7 - 20| = 60 + 60 + 77 + 90 * 3 + 17 + 13 = 497$. We may conclude that case 2 provides the best beta combination to generate the closest solution compared to survey data. We also compare the difference if this household ID 12048694 using case 3 betas, which are the best set of betas for household ID 12023859. $\sum_i L_i = |450 - 510| + |495 - 555| + |1090 - 1110| + |1080 - 1140| + |1207 - 1140| + |1207 - 1140| + |640 - 495| + |7 - 20| = 60 + 60 + 20 + 60 + 67 + 67 + 145 + 13 = 492$. This solution seems a better fit than case 2 but this solution introduces a new travel pattern. The case 3 betas solution suggests that this person will go home after work instead of directly going to shopping. As we mentioned before, we do not have travel data from each node to node, we only implicitly interpret the travel time for unobserved nodes to nodes. Thus, we cannot conclude that case 3 betas fit better than case 1 at current stage.

In theory, we can continue the same process of getting a set of betas for every household then we will have a matrix of betas for the whole survey. Figure 5.14 shows how TUHAPP can be apply in the whole region for every household.

Table 5.18 TUHAPP solution on each case scenario at household ID 12048694

	Observation		Base case		Case 1		Case 2		Case 3	
Activities	T_i	S_i	T_i	S_i	T_i	S_i	T_i	S_i	T_i	S_i
0	510	-	450		450	-	450	-	450	-
1	555	495	495	300	495	420	495	478	495	640
2	1110	20	855	185	975	65	1033	7	1090	7
3	1140	-	1050	-	1050	-	1050	-	1080	-
4	1140	-	1050		1050	-	1050	-	1207	-
5	1140	-	1050		1050	-	1050	-	1207	-
Difference	0		1005		645		497		492	

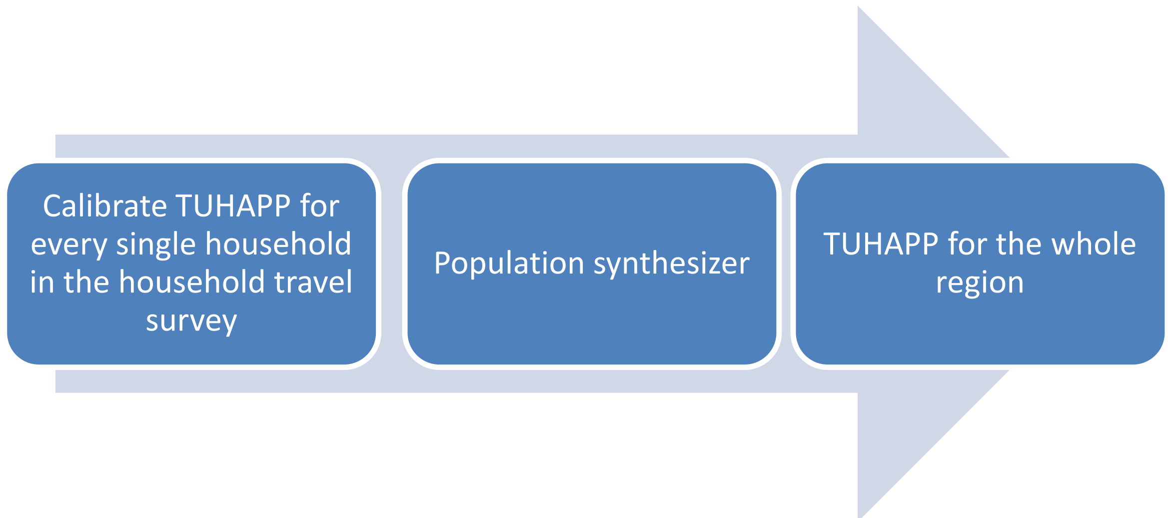

Figure 5.14 TUHAPP as a part of the activity-based model

Conclusion

In this Chapter, we outline how to use TUHAPP as an activity-based model by using 2001 SCAG household travel survey data as an example. We first use linear regression to obtain the parameters of assumed utility functions of activity arrival and utility functions of activity duration. Then, we use heuristic methods to calibrate betas. When we calibrate betas for the examples, we use reported travel times rather than using travel times from the SCAG 2008 RTP model in order not to bring more errors to the calibration process; in actual application these latter values would be assumed. The process of using TUHAPP (UHAPP) is that we first obtain utility functions of activity arrival and utility functions of activity duration, and then we calibrate betas for each household. Once we have betas for each household in the survey, in principle, we can use a population synthesizer to generate betas for the full population in the region. We have shown how TUHAPP (UHAPP) can be used as part of an activity-based demand model. Future research is needed to come up a faster algorithm to calibrate betas; at this point we rely only on a simple heuristic.

Chapter 6 CONCLUSION AND FUTURE RESEARCH

Conclusion

Spurred by the transition from a trip-based four-step model to an activity-based model, a number of activity-based models have been developed and are increasingly being used by MPOs. Our introduction in Chapter 1 has outlined the reasons for choosing HAPP and the problems we need to address in using HAPP as a regional travel demand forecasting tool. In Chapter 2, we compare the differences between our approach toward activity-based demand modeling and that of other researchers. We modify and extend HAPP to UHAPP to incorporate the utility of activity arrival and utility of activity duration in Chapter 3. We extend and reformulate UHAPP as TUHAPP to be able to handle different travel times and travel costs during a day in Chapter 4. We develop a framework for how to use TUHAPP as part of an activity-based demand model in Chapter 5. In this process, the HAPP model has grown from solving a pickup delivery problem with time windows to be a customized, tailored activity-based model, TUHAPP. The linear assumption on utility of activity arrival and utility of activity duration has provided a convenient mechanism for modeling and obtaining solutions for changes in the transportation environment that are policy sensitive. But, the assumed linear form of the utility functions also limits the solution space to be at the intersections of those linear functions. The different distributions of the weight of each objective extend our understanding on modeling inhomogeneous households. A more advanced systematic algorithm is needed to calibrate the distributed weights of each objective. However, even with all of these limitations, TUHAPP is still a far more integrated activity-based demand model than other discrete choice type activity-based demand models. As we have shown in

Chapter 3 and Chapter 4, the methodology of extending HAPP is relatively simple and similar extensions can be adopted to customize TUHAPP to meet special needs.

Future research

TUHAPP is still a linear optimization problem and we know that the linear assumption on utility of arrival time and activity duration preferences may not be accurate. To change TUHAPP into a nonlinear optimization problem is our future research and the difficulty will be put on solution algorithms since nonlinear optimization problems are significantly harder to solve. A middle ground is to divide the utility formulations into finer time intervals to obtain more coefficients for utility functions of activity arrival and activity duration. Also, since TUHAPP can handle time-of-day travel times and travel costs, a feedback loop can be set up which can load the aggregate data of people's departure time, route choice and mode choice from TUHAPP. Moreover, TUHAPP is a deterministic model, in contrast to the uncertainty that is the nature of transportation planning and forecasting. It would be useful to introduce some stochastic elements into TUHAPP. One future research would be to replace the deterministic static travel times with stochastic travel times. Because even though we have time-of-day travel times, actual travel times are never constant for the same time-of-day; a stochastic travel time matrix can address the nature of stochastic traffic conditions and give a more reliable solution than those determined by static travel time inputs. Although we have extended the HAPP models from the demand side and supply side, incorporating other research on HAPP can significantly improve the quality of estimation and the efficiency on getting an optimal solution. The original HAPP formulation uses hard time window constraints to force vehicles or people to arrive in a predetermined time window. We have modified HAPP to be able to capture the utility of people's arrival time preferences, and at the same time, we have given a hard time window constraint for the supply side in the form of business or operation hours for activities. A further extension which is related to transportation accessibility estimation is that, given the same type of candidate locations with different business hours or operation hours, which to choose from. Unlike Kang and Recker's (Kang & Recker, 2013) approach, travel times and travel costs between different location candidates may not be the only location selection criteria, the business hours or operation hours are also important factors for location selection decisions. If most candidate locations are within the same traffic analysis zone, the travel times and travel costs will be the same and no difference will be made in the optimal solution. An extension involving modifying constraints (4-23) with capability for comparing different business hours and operation hours for activities can give policy makers options on regulating commercial business and regular public events. Not only incorporating the location selection problem into TUHAPP, but also with the extension of selecting locations based on their business hours and operation hours are future research directions. Another future research goal is to use a well-designed algorithm to calibrate the distributed weights for each objective component in TUHAPP. Chow and Recker (Chow & Recker, 2012) have shown an inversed optimization approach to estimate parameters on HAPP, but since TUHAPP is more suitable as an activity-based demand model, we will need to make effort to develop a systematic algorithm to calibrate the distributed weights for each household of TUHAPP for the whole survey. The last and the most common issue for most NP-hard problems is finding a faster solution algorithm. Kang and Recker (Kang & Recker, 2013) have introduced a column generation with dynamic programming algorithm to solve the location selection HAPP. Because TUHAPP is an extension and modification of HAPP, we can also introduce similar algorithms to solve TUHAPP. To our best knowledge, Lagrange relaxation can also be introduced to solve TUHAPP due to the existence of inequality constraints. Also, due to the size of TUHAPP, we can decompose the problem to a smaller size, such as by household members. By decomposing a household by members and running TUHAPP for each household member as a subproblem, we can use multithread computing to solve the problem in a more efficient way. There are many issues and questions to be addressed in HAPP before it can be effectively deployed as an activity-based demand model. The growing trend towards activity-based demand models in practice will undoubtedly uncover more questions for researchers to answer. We are looking forward to applying TUHAPP in one of the MPOs regional transportation forecasting models and we believe that the time is near.

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