A Needs-Based Approach to Activity Generation for Travel Demand Analysis

by

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Abstract

This thesis develops a needs-based framework for behavioral enhancement of conventional activity-based travel demand models. Operational activity-based models specify activity generation models based on empirical considerations which are weakly founded in a behavioral theory. This thesis aims to enhance the specification of the activity generation models by developing the conceptual and analytical relationship between individuals' activity choices and need-satisfaction.

The theory of needs hypothesizes that individuals conduct activities to satisfy their needs. Each activity that an individual conducts may satisfy one or several of their needs. Conversely, each need may be satisfied by one or several activities. This thesis models an individual's choice of activity dimensions including frequency, sequence, location, mode, time-of-travel, etc. as one that maximizes his/her need-satisfaction.

A conceptual model of the relationship between needs and activities is developed based on inventory theory. Every need is associated with a psychological inventory that reflects the level of satisfaction with respect to the need. When an activity that satisfies a need is conducted, the need is satisfied and the corresponding psychological inventory is replenished by a quantity called the activity production. Over time, this inventory gets consumed and the need builds up. The choice of activity dimensions is modeled as a psychological inventory maximizing (i.e. utility-maximizing) problem, subject to time and cost budget constraints. The framework also accounts for satiation in need-satisfaction.

An analytical model is formulated, solved and empirically estimated for a single need and the activity that satisfies the need under steady-state conditions. The problem is solved in two stages, for discrete (location) and continuous (duration and frequency) decision variables. The properties of the general solution are studied, and then explored for a translog form of the activity production function. An empirical estimation method that can be applied to single day travel diary data is proposed and validated using Monte-Carlo experiments. The model is empirically estimated using standard travel diary data from the Denver metropolitan area. Estimation results indicate the potential of the needs-based approach to enrich the specification of activity generation models in conventional activity-based model systems.

A conceptual framework to extend the single need model is discussed. Extensions to models of multiple needs that capture interactions between different needs are also discussed.

The flexible framework can also be extended to model social interactions including intra-household activity allocation and joint activity participation by households and social circles. An extension to a dynamic needs-based activity generation model is also discussed, which may be integrated with transportation simulators to predict individuals' activity choices in response to real-time information.

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1 Introduction

This thesis focuses on behavioral enhancements to the conventional activity-based approach to travel demand modeling. It studies the relationship between an individual's activity choices and need-satisfaction. Based on the theory of needs, it develops a conceptual framework that describes an individual's activity choices as motivated by the desire to satisfy human needs. An analytical model is formulated based on this conceptual framework, that describes an individual's activity choices as motivated by the desire to maximize his/her need-satisfaction. This framework can be integrated into conventional activity-based travel demand models to enhance their behavioral realism. This chapter describes the motivation for this thesis, summarizes the key contributions, and presents the thesis organization.

1.1 Motivation

The travel demand forecasting systems used in urban metropolitan areas in the United States in the 1950's and 1960's, which served as a support system to aid large infrastructure investment decisions, were simplistic with few explanatory variables and estimated from aggregate data. However, as the boom in infrastructure investments subsided, planners focused on better management of existing systems in response to issues like congestion, pollution, suburban sprawl, etc. The impacts of policy measures proposed to counter the new problems at hand were predicted poorly by aggregate demand models, which are not sensitive to policy alternatives. This led to the development of disaggregate models based on utility-maximizing econometric theory which are estimated using individual or household data and can explicitly account for the heterogeneity in individual and household travel choices. The vast amount of literature about the theory of disaggregate choice modeling for travel demand forecasting is well documented (e.g. see Ben-Akiva and Lerman, 1985 for an early review, and McFadden, 2000 for a more recent review).

Several methodological improvements were made to the disaggregate travel demand modeling approaches through the 1970's and 1980's, and were operationalised in practical model systems by metropolitan planning organizations. Early disaggregate model systems were trip-based, and considered a trip - defined as a commute from an origin activity center (e.g. home) to a destination activity center (e.g. work place) with no stops in between to conduct other activities - as the basic unit of modeling. Using unlinked trips as the basic unit was found to be behaviorally restrictive since it did not account for interaction between various trips conducted by the same individual. As the limitations of the trip-based approach were realized, researchers and practitioners adopted a tour-based approach, where a tour - defined as a sequence of trips starting from a location (e.g. home) and ending at the same location (i.e. home), and consisting of several stops to conduct activities outside the origin - is the basic unit of modeling. While tour-based models provide a better representation of travel decisions than trip-based models, they still fail to capture the interactions between different tours an individual makes on the same day.

As the limitations of tour-based model systems were realized, researchers focused on developing model systems that capture an individual's travel choices at the level of a day. These model systems, in a form known as activity-based model systems, are increasingly being adopted by transportation planning organizations across the world, particularly in the United States, to forecast travel demand in urban areas. These models are motivated by the notion that demand for travel is derived from the demand for activities, and therefore, the latter should be modeled as a component of the activity scheduling decision. Hägerstrand (1970) laid the foundation for the activity-based approach to travel demand modeling, where he argues that individuals travel to conduct activities and make these decisions subject to spatio-temporal constraints. In contrast to conventional trip-based or tour-based travel demand models, activity-based models predict more realistically the human response to changes in transportation and land-use systems.

Figure 1.1 provides a framework to study the decisions made by households and individuals relevant to their travel during different timeframes (Ben-Akiva et al., 1996). In the long term, households and individuals re-evaluate their mobility and lifestyle decisions. For example, once in every two or three years, individuals may review their level of satisfaction with their current home location, work location, auto ownership, etc., and re-evaluate these choices in the context of changing land-use and economic development in the urban area. They then make new choices on where to live and work, whether to own a car or use public transportation, etc. Once these choices have been made, they plan their daily activities and travel in the medium term, subject to availability of time and income. These choices, namely activity and travel scheduling choices, determine the set of activities that members of a household participate in, including the allocation of activities among members, the frequency, location, duration and sequence of activities. They also then plan their travel to participate in these activities, including departure time and mode. Given a set of lifestyle and mobility choices made in the long term, individuals change their activity and travel patterns in response to changes in the transportation system. For example, the introduction of congestion pricing in an urban area during the peak period is likely to cause individuals to change their activity and travel patterns. This could vary all the way from changing the route that they take to work on a daily basis, or changing the time-of-travel to work to off-peak periods when there is no congestion price, or reducing the extent of discretionary activities conducted during the peak period that require travel. Finally, when they actually set out to execute this plan, they may encounter unexpected events both during their travel and while conducting activities. Consequently, they may reschedule their activity and travel patterns to adapt to the transportation network conditions in the short term. For example, while an individual might have planned to conduct shopping on the way back home from work, extremely congested traffic conditions might force the individual to cancel the shopping activity and return home without conducting shopping. The framework also models the effect of transportation system performance on land-use patterns and economic development in the urban area, which in turn affect an individual's mobility and lifestyle choices in the long term.

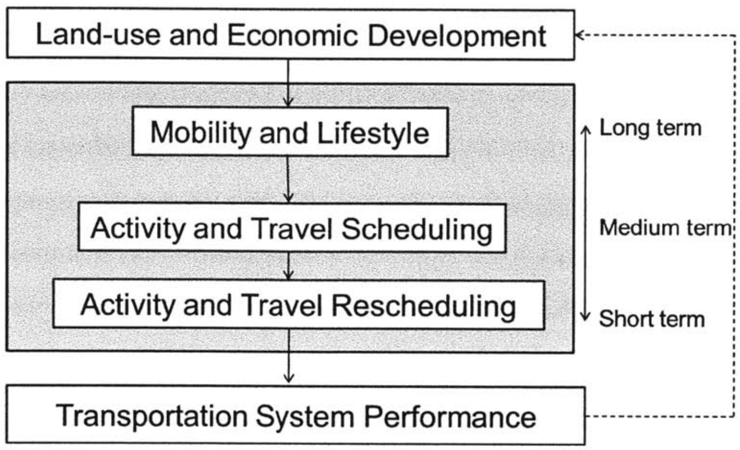

Figure 1.1: Framework for urban travel decisions (Ben-Akiva et al., 1996)

The focus of this thesis is on the activity and travel scheduling decisions which affect the demand for transportation services in an urban area. Several operational travel demand forecasting systems model these decisions in a form known as the day activity schedule approach. (Ben-Akiva et al., 1996; Bowman, 1998). The activity schedule approach first generates a set of activities an individual performs on a day (e.g number of activities performed on tours and stops by purpose), and then models the travel dimensions including destination, mode, and time-of-travel for tours and trips, given an activity pattern (see Figure 1.2). Based on the priority of the primary activity on each tour, tours are classified as primary tour (i.e. most important tour of the day) and secondary tours. The choices determined by the upper level models (e.g. activity pattern models) also account for the various alternatives available at the lower levels (e.g. tour level) by including logsum variables in their utility functions (see Ben-Akiva and Lerman, 1985 for logsum variables and nested logit models). This model system is reviewed in Chapter 2.

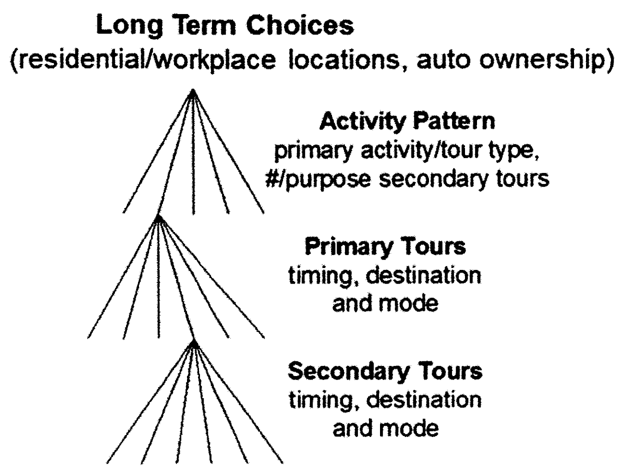

Figure 1.2: Day activity schedule approach to travel demand modeling (adapted from Bowman, 1998)

Several modeling developments have been incorporated into these models over the last decade, including better representations of household joint decisions (see Chapter 2 for a detailed review). Yet, the specification of the activity pattern (generation) model in operational activity-based model systems is weakly founded in a behavioral theory, and combines a number of socio-economic, demographic, lifestyle, and accessibility variables based on empirical considerations (Abou-Zeid and Ben-Akiva, 2012). The extensions to this framework that seek to enhance the specification of the activity generation model may broadly be classified into two groups as econometric and behavioral. The first extension maintains the standard activity pattern utility specification but adds information about the utility using well-being measures. By using individuals' self-reported satisfaction levels with their chosen activity patterns as indicators of the utility of these patterns (through measurement equations), it is anticipated that the resulting model will be more efficient than one without well-being measures (see Abou-Zeid (2009), for an example in a mode choice context).

The second extension aims at enhancing the activity generation models by specifying models which are more strongly founded in a behavioral theory. Based on the theory of needs (Maslow, 1943), Chapin (1974) described that individuals make activity choices to satisfy various needs like survival, social encounters, and ego gratification. Thereafter, several studies have discussed the conceptual relationship between human needs and activity participation, and the role of time and budget constraints in limiting activity participation and the extent of need-satisfaction individuals attain. The idea of a limiting time constraint has been formulated in models explaining trip chaining and joint models of multiple dimensions of activity choice including time-of-travel, sequence, mode, etc. (see Adler and Ben-Akiva (1979); Eluru et al. (2010))

However, most studies that explore the relationship between needs and activities are conceptual, rule-based, or generally do not develop the needs-activity relationships into an analytical model (Adler and Ben-Akiva, 1979; Märki et al., 2011; Nijland et al., 2010; Westelius, 1972). Arentze et al. (2009b) developed an analytical model of needs and activity generation where the utility of an activity is affected by the satisfaction of the need and an activity is performed if its utility exceeds a certain threshold (representing time pressure). The model predicts which activities are performed on a given day, but not their sequence, location, duration, start times, and travel modes. A method to estimate the model using one-day household travel survey data is proposed, which, however, requires knowledge of the last time an activity was conducted before the survey day, either based on a random draw (Arentze et al., 2011) or based on an extended travel survey (Nijland et al., 2012).

Given the state of art and practice of activity-based models, there is scope to improve the specification of the activity generation models, which are critical to the predictive capability of the day activity schedule approach. To this end, this thesis develops a framework for needs-based models of activity generation for travel demand modeling. It aims to develop analytical models that have greater behavioral realism than conventional activity generation models, and can be empirically estimated from standard travel diary data.

1.2 Key Contributions

This thesis models the relationship between activity participation and need-satisfaction. Based on the theory of needs, it describes individuals' activity participation as aimed at satisfying their needs (e.g. physiological, safety, etc.). Individuals conduct several activities, each of which satisfies one or more of their needs. Within this framework, it models individuals' choice of activity dimensions (e.g. frequencies, locations, sequence, durations, etc.) as one that maximizes their need-satisfaction. This approach draws on ideas from inventory theory (as in some other studies on needs) to conceptualize the evolution of the need. Every need is associated with a "psychological inventory", which is viewed as an indicator of need-satisfaction, and is replenished, by a quantity called activity production, each time an individual conducts an activity that satisfies the need; the psychological inventory depletes over time as the need builds up. A conceptual formulation of a needs-based model of activity generation is developed. Based on this conceptual formulation, an analytical formulation of a needs-based psychological inventory maximizing model of activity location, duration, and frequency is developed. In this thesis, a solution of the model for a single need and the activity that satisfies the need is presented, and its properties are studied. An estimation procedure is developed that can be applied to single day travel diary data with no knowledge about the last time an activity was conducted. The model is verified empirically using standard travel diary data from the Denver Metropolitan Area.

The models developed in this thesis integrate key ideas from consumer choice theory and the theory of needs to enhance the specification of conventional based models. Several behavioral enhancements, including heterogeneity in individuals' characteristics (e.g. time availability to conduct activities, rate of consumption of psychological inventory of need, etc.), resource constraints (e.g. limited availability of time and money), and satiation (i.e. decreasing marginal returns from conducting the activity for longer durations) are incorporated to improve the behavioral richness. A conceptual framework to extend the single need - single activity analytical model developed and estimated in this thesis to the general case of multiple needs for an individual is presented. The framework is extendable to develop models of social interactions including intra-household activity allocation and joint activity participation. Moreover, the framework can be extended to develop models of dynamic and real time activity choices, which can be integrated with transportation and traffic simulators to capture more realistically the short term activity and travel rescheduling decisions in response to transportation network performance (as illustrated in Figure 1.1).

The needs-based approach developed in this thesis is promising and has the potential to improve the behavioral realism of conventional activity-based models.

1.3 Thesis Organization

This thesis is organized as follows.

Chapter 2 reviews the background material to this study. It presents a review of the various trip-based, tour-based and activity-based approaches to modeling travel demand. It also reviews econometric advances in the area of discrete choice modeling which have been incorporated in activity-based modeling to enhance the specification, including heterogeneity among individuals, and use of well-being indicators through measurement equations. The relationship between needs and activities as described in the literature is also reviewed in this chapter to motivate the needs-based approach developed in this thesis.

Chapter 3 models the relationship between an individual's need-satisfaction and activity participation. The notion of "psychological inventory" as an indicator of an individual's level of satisfaction with respect to a need is presented to provide a framework for the analytical models developed in this thesis. In this framework, an individual conducts activities to satisfy his/her needs, and replenishes his/her psychological inventory by a quantity called the "activity production" each time he/she conducts an activity that satisfies a need. The individual's needs build up over time, and the psychological inventory depletes when this happens. A steady-state optimization model is formulated that hypothesizes that individuals choose their activity dimensions (e.g. sequence, location, duration, expenditure, and frequency) in a way that maximizes their need-satisfaction. A solution procedure is developed for the case of a single need and the activity that satisfies the need. The solution properties are studied, and explored for a translog functional form of the activity (inventory) production function.

Chapter 4 develops an empirical model that can be estimated from standard travel diary data. A likelihood estimator is developed for the joint choice of activity location, duration, and frequency. Results from a Monte-Carlo experiment are presented, that show that the true parameters can be recovered from observable data. Finally, a case study using travel diary data from the Denver Metropolitan Area is presented. Estimation results indicate the potential of the needs-based approach to enrich the specification of activity generation models in conventional activity-based model systems.

Chapter 5 discusses a conceptual framework to extend the model developed in Chapters 3 and 4. Specifically, it discusses enhancements to the single need - single activity model, and the conceptual issues with respect to extending it to multiple activities and needs under steady-state conditions. It also provides a discussion of the dynamic formulation of the needs-based model that can be used to model the activity and travel rescheduling decisions described in Section 1.1.

Chapter 6 concludes the thesis by summarizing the objectives, approach, and key contributions of this research. It discusses the policy implications and the limitations of the research, and directions for future research.

2 Literature Review

This chapter presents a review of the literature in the areas of travel demand analysis and behavioral modeling that are relevant to this thesis. Section 2.1 reviews various disaggregate travel demand forecasting approaches. Section 2.2 presents a review of a few operational activity-based demand model systems, which this thesis aims to improve. Recent studies that have tried to enhance the specification of activity-based models are reviewed in Section 2.3 to provide the context for this thesis. Finally, the state of the needs-based approach, which is the primary focus of this thesis, is reviewed in Section 2.4. It reviews qualitative studies and critiques the existing analytical needs-based models. Finally, Section 2.5 concludes the literature review.

2.1 Disaggregate Travel Demand Forecasting Approaches

As described in Chapter 1, the disaggregate modeling approach to travel demand analysis has been in practice in the United States since the 1970's. This class of models is estimated using data about individual or household choices, and capture the heterogeneity in individuals' decision-making process. Through the 1970's and 1980's, several methodological improvements were made to the disaggregate travel demand modeling approaches, which were operationalised in practical model systems by metropolitan planning organizations. While a brief review of the early disaggregate model systems is presented here, the interested reader is referred to Bowman (1995) for a detailed review of these systems.

Early disaggregate model systems were trip-based, and considered a trip - defined as a commute from an origin activity center (e.g. home) to a destination activity center (e.g. work place) with no stops in between to conduct other activities - as the basic unit of modeling. While these models shared the basic unit of modeling, the trip, with aggregate model systems, their strength lied in the fact that they incorporated individual and household related socioeconomic variables to predict better the impact of policy decisions. However, since the trips modeled by these models were unlinked, the models were limited in their predictive power as they failed to capture inter-trip interactions in an individual's decision making process. The earliest enhancement to this system was provided in the Metropolitan Transportation Commission (MTC) model system developed for the San Francisco Bay area (Ruiter and Ben-Akiva, 1978) which modeled trip chains. Horowitz (1980) developed an integrated trip frequency, destination and mode choice model that enhanced the trip-based approach by jointly modeling several dimensions of individuals' trips.

With the understanding of trip chaining gaining greater importance, researchers shifted focus to a tour-based approach, where a tour - defined as a sequence of trips starting from a location (e.g. home) and ending at the same location (i.e. home), and consisting of several stops to conduct activities outside the origin - was the basic unit of modeling. The National Model System for Traffic and Transport of the Netherlands developed by the The Hague Consulting Group (1992) is an example of a tour-based system. Other tour-based model systems include the Stockholm tour-based model system in Sweden (Algers et al., 1991), the Salerno tour-based model system in Italy, and the Italian Transportation System tour-based model system (Cascetta et al., 1993; Cascetta and Biggiero, 1997).

The tour-based approach, while more comprehensive than the trip-based approach, still fails to capture interactions between various tours carried out by the same individual. Focus shifted to modeling individuals' travel schedules at the level of a day, explicitly capturing interaction between various tours carried out by the same individual. Complex models of activity participation, time use and intra-household joint decisions were developed (see, for example, Adler and Ben-Akiva, 1979; Ben-Akiva et al., 1980, reviewed in the following section). As models of daily travel patterns were developed, modeling the motivation for travel, understanding the role of household and lifestyle conditions on individual decisions, and the dynamic interaction of travel decisions in response to changing conditions also gained importance. This led to the development of a modeling approach in which travel decisions are components of a broader activity scheduling decision bound by time, space and monetary constraints, now commonly referred to as the activity-based approach. A review of the activity-based modeling approach is presented in the next section.

2.2 Activity-based Approaches

The foundations of activity-based approaches are attributed to Hägerstrand (1970), where he describes the relationship between activity participation and the time-space constraints that affect transportation choices. The interested reader is referred to Damm (1983), Golob and Golob (1983) and Kitamura (1988) for a review of the history of activity-based models, and to Pinjari and Bhat (2011) for a more recent review of the activity-based approach. The general notion underscored by all these studies is that travel demand is derived from the demand for activities, and so must be modeled in a larger framework that considers both activity and travel choices of individuals and households (see, for example, Chapin, 1974; Jones et al., 1983; Pas, 1984; Goodwin et al., 1990). Since the primary objective of this thesis is enhancing the activity-based approach to travel forecasting, this section provides a review of the precursors to activity-based models, and operational and prototype activity-based model systems. The operational systems are representative of the best current practice worldwide, while the prototypes demonstrate various aspects of the current frontier in model development.

2.2.1 Precursors to Activity-based Models

Among the earliest analytical models to model the relationship between individuals' daily activity and travel patterns were the two interrelated models developed by Ben-Akiva et al. (1980). While the first group of models focus on modeling activity duration and time budgeting by adults in a household amongst shopping, social and recreational activities, the second group of models focus on activity scheduling, reflecting the daily pattern of activities of adult workers over five time periods defined with respect to home and work. Each group of models treats the participation and duration decisions jointly, using a joint discrete/continuous choice model. Both groups of models incorporate an accessibility variable from a conditional mode and destination choice model. This measure of the availability and ease of transportation to the modeled activity is specific to the worker's home and work locations, as well as the activity purpose. The model provides a framework to model intra-household activity participation jointly with time allocation (duration), and incorporates measures of accessibility. However, it is limited to non-work activities on a work day.

Adler and Ben-Akiva (1979) developed a model of daily non-work travel patterns. In this model, the choice of travel pattern is modeled as a single complex decision, in which many component decisions together define a day's travel. The model is implemented as a multinomial logit model. Each alternative in the model is defined as a specific combination of 1) number of tours, 2) number of destinations, 3) location for each destination, and 4) the travel mode for each tour. While this model jointly models the daily travel pattern choice as a single complex decision, it does not represent activity duration and timing in the travel pattern decision.

While these early models successfully modeled a full day's travel pattern, they are considered precursors to activity-based models, since they did not link activity generation to travel demand. The next section presents a review of full-fledged activity-based models, which were motivated by the precursors and are currently used by several metropolitan planning organizations around the world.

2.2.2 Activity-based Models

Full-fledged activity-based travel demand model systems, with integrated modeling of activity and travel choices were in development by the 1990's. A general framework that describes the relationship between activity and travel decisions was provided by Ben-Akiva et al. (1996) (also see Kitamura et al., 1996 for an alternate framework of a sequenced activity-mobility simulator). A review of activity-based models and their potential in modeling systems to assist in policy decisions was presented by Axhausen (2000). Over the last two decades, several operational model systems have been developed, which according to Pinjari and Bhat (2011), can broadly be classified into one of the following categories: (1) Rule-based model systems, and (2) Utility maximization based econometric model systems. Several other approaches, including: (a) Time-space prisms and constraints, and (b) operations research/mathematical programming approaches have been employed, either in combination with the above or separately, to develop activity-based model systems. Pinjari and Bhat (2011) also note that most operational model systems are based on a combination of two or more of these approaches, rather than exclusively based on any one of them. In this section, a brief review of the rule-based and econometric models is presented. An approach called the day activity schedule approach, which this thesis seeks to improve upon, is also reviewed in this section.

2.2.2.1 Rule-based Model Systems

Gärling et al. (1994) defined rule-based model systems as those that specify how a choice is made based on a set of rules in the form of condition-action (if-then) pairs. This approach is based on the notion that individuals use heuristics to make decisions about travel and activities based on the context, rather than thinking about the choice as an outcome of utility maximization (Timmermans et al., 2002). Consequently, these models provide an exhaustive set of rules to specify how decisions are made under different possible contexts. While this approach is hailed for its simplicity, it is limited by the modeler's ability to determine the factors that affect activity and travel decisions. Moreover, most model systems based on this approach consider activity generation to be exogenous (provided by an external source), and focus only on the scheduling or sequencing of activities. Even for activity scheduling and sequencing, it is difficult to enumerate all the decision rules underlying such a complex process. However, these model systems have been successfully implemented in practice despite these limitations, and this section reviews three rule-based model systems, namely STARCHILD, ALBATROSS and TASHA.

1. Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions (STARCHILD, see Recker et al., 1986a and 1986b) is the earliest example of a full-fledged rule-based model that provides a unified framework for activity and travel demand analysis. The model uses an activity program, defined as a set of activities that an individual wants to conduct in a given timeframe (without a known schedule), as an exogeneous input. Using this input, the model generates a feasible set of activity patterns, which includes the activities to be conducted with their sequence, by using a set of rules. It incorporates time-space, household and transportation system constraints in the enumeration of feasible daily activity patterns, and incorporates activity pattern attributes such as available free time, risk of missing important activities and availability of family time in the activity pattern choice model. Finally, it employs a

utility maximizing framework to explain the choice of an activity pattern from this feasible set. It is the earliest example of a model system that could generate disaggregate travel demand based on an activity program. However, the fact that the model system assumes an externally supplied detailed activity program, making no provision for the modeling of activity location or duration, is a weakness.

2. A Learning-BAsed TRansportation Oriented Simulation System (ALBATROSS, see Arentze and Timmermans, 2004) is a rule-based model system that exploits the notion of rigid and flexible activities to schedule activities. Based on an activity diary that describes an individual's characteristics, and activity sequence, purpose, timing and duration, it generates an activity schedule by combining this information with a set of constraints, land-use data and transportation system characteristics. It first schedules rigid activities (e.g. work, school, picking up a child from day care, etc.) and then goes on to add flexible activities (e.g. shopping, recreation, etc.). Once the activity pattern is known with the sequence of trips, the model determines timing, trip chaining patterns, mode choice and destinations. The model allows for resequencing of activities during the scheduling process, to resolve conflicts. ALBATROSS uses observed data to derive the heuristics, rather than specifying them based on ad-hoc rules. However, since there is no theoretical basis for the choice of heuristics, the applicability of the model is limited.

3. Travel and Activity Scheduler for Household Agents (TASHA, see Miller and Roorda, 2003; Roorda et al., 2008) is an advanced model system that schedules activities with the objective of conducting "projects". Projects are defined as a set of coordinated activities performed to achieve a common goal. For example, activities such as shopping for food, preparing meals, and having a dinner with guests are all tied together by a common goal, which is to hold a dinner party. For each project, a list of activity episodes is generated that can potentially be executed in the context of the project. The model also recognizes and incorporates the idea that activity scheduling is a path-dependent process and the final outcome of the scheduling process depends on the order

in which decisions are made. Thus, the agenda is dynamically augmented with further details (such as add an activity, or delete an activity either because it is executed or canceled) until the project's purpose is fulfilled. Innovative and intuitive concepts such as activity precedence and scheduling conflict resolution are utilized to inform the development of path dependent (or dynamic) schedule planning and adjustment (or rescheduling) strategies and household-level interdependencies.

While rule-based model systems have been used, their choice of rules based on empirical considerations has repeatedly been questioned. Moons et al. (2005) evaluate existing rule-based model systems, particularly ALBATROSS, to study the impact of simplifications employed in rule-based model systems, to conclude that identifying the factors that affect scheduling decisions is key to good performance of the heuristics chosen. On the other hand, the econometric model systems discussed in the next section are considered superior since they are based on utility maximizing consumer theory.

2.2.2.2 Utility Maximization-based Model Systems

Based on the theory of a rational utility-maximizing consumer, these models predict activity and travel decisions using (discrete and continuous logit type) econometric models. In addition to the discrete choice models, several model systems employ other econometric structures, including hazard-based duration structures, and ordered response structures to model various activity-travel decisions. In all, these model systems employ econometric systems of equations (most of which are utility maximization-based) to capture relationships between individual-level socio-demographics and activity-travel environment attributes on the one hand and the observed activity-travel decision outcomes on the other. Since they do not impose any externally supplied ad-hoc rules, but rather estimate the model parameters from observed data, these models are considered superior to rule-based models.

An econometric activity-based travel demand model system was operationalized in an approach known as the day activity schedule approach by Bowman (1998) (see also, Bowman and Ben-Akiva, 2001). This approach has now been adopted by several metropolitan planning organizations in the United States including Portland (Bowman et al., 1998), San Francisco (Bradley et al., 2001), New York (Vovsha et al., 2002), and Sacramento (Bowman et al., 2006). In this approach, an individual's activity pattern is generated for a day, and then the travel choices to conduct these activities are determined by forming tours and trips. The later decisions (e.g. travel choices) are conditional upon the earlier decisions (e.g. activity choices), while the earlier decisions account for the later decisions by including measures of accessibility. The features of the Sacramento model are described in Section 2.2.3 as an example of a day activity schedule based model.

Other econometric model systems that have been developed and operationalized since the day activity schedule approach include the Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP, see Pinjari et al., 2008) and the Florida Activity Mobility Simulator (FAMOS, see Pendyala et al., 2005).

CEMDAP is a continuous time activity-travel forecasting system that is based on a range of discrete choice, hazard-based duration, and regression based econometric models. While similar in hierarchy to the day activity schedule model, CEMDAP additionally provides for separate frameworks for representing and modeling workers' (and school going children's) and non-worker's (and non-school going children's) choices. It also models intra-household interactions between parents and children.

FAMOS is similar to CEMDAP in the explicit recognition of space-time constraints and the continuous time nature of the modeling system. Hägerstrand's space-time prisms are utilized to represent and model the spatial and temporal constraints under which individuals undertake activities and trips (hence, the name prism-constrained activity travel simulator). The boundaries (or frontiers) of these space-time prisms, within which the individual activity travel patterns must take place, are determined by using stochastic frontier models (see Pendyala et al., 2002). Subsequently, the activity-travel patterns are simulated within the boundaries of the space-time prisms.

This section provided a brief review of various activity-based modeling approaches that are currently in practice. Examples of operational model systems based on the approaches, broadly classified as rule-based and econometric, were provided. The next section reviews the day activity schedule approach, which is widely used by practitioners.

2.2.3 The Day Activity Schedule Approach

The overall framework for model systems based on the day activity schedule appoach developed by Ben-Akiva et al. (1996) is as shown in Figure 1.2. This section presents a review of the Sacramento model (Bowman et al., 2006), called DaySim, as an example of a day activity schedule based model system. DaySim consists of an econometric micro-simulation system with a three-tier hierarchy of: (1) Day-pattern level choice models, (2) Tour-level choice models, and (3) Trip/Stop-level choice models.

The day-pattern level models consist of the day activity pattern model and the number of tours model. These models predict: (a) the occurrence (and the number) of home-based tours (i.e., tours that originate and end at home) by the purpose of the main/primary activity on the tour, classified into the following seven activity purposes: work, school, escort, personal business, shopping, meal, and social/recreational, and (b) the occurrence of additional stops/trips that may occur for these seven purposes (as 0 or 1+ stops).

The tour-level models predict the primary destination (i.e., the destination of the primary activity for which this tour is made), travel mode, time-of-travel of travel (i.e., time of arrival at, and time of departure from primary destination), and the number of additional stops by purpose (other than the primary activity) for all tours. Tour-level models also include a work-based sub-tour (i.e., a tour that originates and ends at work) generation model that predicts the number (and purpose) of work-based tours for each home-based work tour the individual undertakes.

The trip-level (or stop level) models predict the trip location (or destination of the stop), mode, and time-of-travel for each of the trips (to stops other than the primary activity of a tour) generated in the previous steps. An individual's daily activity and travel plan, which consists of a list of activities with their purpose, location, and the mode, and time-of-travel for the trip undertaken to reach these activities, is created by these models, thereby providing a fully disaggregate representation of travel demand.

The key strength of the day activity schedule approach lies in its ability to provide an integrated representation of activity and travel choices, related in the model framework through a tree structure with accessibility logsums. This approach has received a lot of attention over the last decade, and has constantly been enhanced in several ways. The next section discusses these enhancements.

2.3 Enhancements to Activity-based Approach

This section deals with recent advances in the area of activity-based modeling that have aimed at improving the approaches reviewed in Section 2.2. The key areas in which these models have been improved include: (1) modeling intra-household interactions and joint activity participation, (2) modeling time use and budgeting to account for limited resource availability, (3) modeling multi-day activity schedules, (4) modeling activity planning, (5) incorporation of well-being indicators to enhance the econometric specification, and (6) behavioral enhancements to activity-based models. The first five enhancements are discussed in this section, while the last one is discussed in the next section.

2.3.1 Intra-household Interactions

While early activity-based travel studies and operational models ignored the interactions between individuals within a household, more recent studies and models have emphasized the need to explicitly consider such interactions and model joint activity participation within a household. Bhat et al. (2011) developed a model of intra-household interactions, motivated by evidence that shows that individuals in a household do not make activity decisions in isolation (see, for example, Gliebe and Koppelman, 2002). Moreover, there is some rigidity involved in joint activities, since it involves synchronization of activity and travel schedules of multiple individuals in the household (Timmermans et al., 2002). Finally, there is also evidence that joint household activities are systematically different from individual activities with respect to activity and travel dimensions (Srinivasan and Bhat, 2006; Vovsha et al., 2003). These studies argue that joint activities typically involve longer trips, activities with longer durations, using larger and more spacious vehicles. Consequently, modeling intra-household joint activity participation has received much attention. Simplistic models include some measure of household interactions in the utility functions (e.g. by including variables such as presence of children in the household, number of household adults or workers, etc.). Bhat et al. (2011) estimated a household-level activity pattern generation model that predicts, for a typical weekday, the independent and joint activity participation decisions of all individuals (adults and children) in a household, for all types of households, for all combinations of individuals participating in joint activities, and for all disaggregate-level activity purposes. A multiple discrete continuous extreme value model framework is used (Bhat, 2008), wherein the household's utility from performing several activities is maximized by determining the optimal allocation of time to different activities. However, it is important to note that there is a trade-off between the realism added by explicitly modeling household interactions and the resulting computational and model complexity.

2.3.2 Time Use and Budgeting

Extensions that deal with time use and budgeting focus on studying how limited time availability drives activity and travel choices of individuals. The travel pattern model developed by Adler and Ben-Akiva (1979) is an early example of a model that accounted explicitly for the relationship between travel choices and time use, by modeling trip chaining behavior. More recently, several studies have modeled explicitly the impact of time budgeting on activity participation. Using the multiple discrete continuous choice framework developed by Bhat (2008), Pinjari and Bhat (2010) developed a model of non-worker activity time-use and time-of-travel choices. Under this framework, an individual is modeled as choosing one or more alternatives from a choice set consisting of alternatives that are distinguished by the activity purpose, time-of-travel, and mode. Additionally, activity duration is modeled as a continuous variable, and is bound by a time constraint that ensures that the total time spent on all activities, in-house and out-of-house, does not exceed the total time available on any day. The location choice for these activities is introduced as a nested choice, conditional upon the purpose, mode and time, and is modeled as a multinomial choice model. While these models capture an important aspect of activity participation, i.e. limited time availability and time budgeting, they do not attempt to model the underlying behavioral processes that motivate activity participation and choices.

2.3.3 Multi-day Activity Generation

The importance of modeling activity choices across multiple days is well recognized in the literature. Kitamura (1988) argued for the importance of modeling multi-day activity choices and questioned if unbiased representation of travel behaviour is possible at all with one-day data because of the day-to-day variations. The lack of progress in this direction, however, has been explained by limited availability of data. Most travel surveys are restricted to single day travel diary records, and limit the ability to model activity choices (especially frequency choices) across multiple days.

However, several modelers have attempted to collect multi-day data and formulate models. For example, Hirsh et al. (1986) developed a dynamic model of weekly activity pattern. In this study, an activity program for a fixed time period (e.g. a week), defined as a set of activities to be conducted without its schedule, is taken as the input to determine the activity patterns, defined as the activities with a known schedule. The activity schedule choices are determined by breaking the overall time period (i.e. the week) into smaller time periods (e.g. a day). Initially, a plan is made for each of the smaller time periods (days), and the plan for the first time period (day) is executed. After the plan is executed, the plan for the remaining days is updated and the updated plan for the second day is executed. This process is iteratively carried out till the end of the week. The model uses a logit structure and allows for interaction between different days through interaction terms in the utility functions. An empirical model is estimated for an individual's weekly shopping activities.

A significant study in this direction is the Mobidrive project, which collected travel diary data for a continuous period of six weeks. The data included detailed activity and travel information (including locations, durations, expenditures, times-of-travel, etc.) on all days during the 6-week period (Axhausen et al., 2002). This dataset has been used extensively to study temporal variation in activity-choices including day-to-day variation, dynamic activity frequency choice, etc. (see, for example, Schönfelder and Axhausen, 2001; Susilo and Kitamura, 2005; Chikaraishi et al., 2010).

More recently, interest has been regained in modeling multi-day activity generation in the context of needs-based approaches. The models that fall under this category are reviewed in Section 2.4.

2.3.4 Activity Planning

Recently, research effort has been focused on modeling activity planning decisions. This body of literature models various dimensions of activity choices and studies the order in which various dimensions are planned. First, several studies assume that individuals' activities may be broadly classified as fixed (e.g. work, school) and flexible (e.g. shopping, recreational). This notion has been questioned in the context of changing lifestyles with a greater need for work-life balance, wherein individuals have the option of working from home with flexible timings. Moreover, conventional model systems determine the order in which activity dimensions (e.g. location, mode, time-of-travel) are chosen based on rules or empirically. Activity planning research has focused on modeling this planning process between planning of activities and their execution.

Doherty et al. (2004) collected data on activity planning by conducting an extended activity scheduling survey. In this study, respondents were required to record their activity schedule plans during a 7-day period. On each day, individuals recorded all the activities they planned to conduct through the week, including the level of detail to which different dimensions had been decided. For example, an individual could record on Day 1 that he/she would perform shopping on Day 5 or 6 at a specific location. In this case, the location was determined with certainty, while the day and exact time-of-travel were not specified exactly. Other decisions including mode, activity duration, etc. were not made at this point. Similarly, on each day, the individual updated his/her plan for the remaining week, and additionally reported the activities that were conducted on that day. At the end of the survey, multi-day travel data including activity planning and scheduling information were available.

Kourous and Doherty (2006) developed hazard models to predict the duration of time between planning and execution of pre-planned activities based on attributes of activities and characteristics of decision-makers. The model was estimated with data collected by Doherty et al. (2004). The study reveals that several overriding personal and situational factors, apart from activity purpose, play an important role in the planning decisions. The extension of activity-based models to incorporate activity planning decisions is important to enrich the policy sensitiveness of these models.

2.3.5 Including Well-being and Happiness Indicators

There is evidence in the literature that suggests that activity and travel choices are made to maintain or enhance well-being (see, for example, Abou-Zeid and Ben-Akiva, 2012). It is possible to enhance the specification of activity-based models by including explicitly measures of activity and travel well-being and happiness. There are a large number of studies that have analyzed commute stress and used quantitative methods to explain happiness as a function of causes and correlates using regressions. Happiness has also been modeled within the framework of discrete choice models as an additional explanatory variable in the utility (Duarte et al., 2008). A detailed review of these approaches may be found in Abou-Zeid (2009), where a framework is developed to use happiness measures as indicators of utility in random utility models. The study proposes model frameworks that include additional happiness indicators, collected through additional questions about decision-makers' happiness and satisfaction with their activity and travel choices asked during a travel survey. A case study is presented in the context of mode choice models where it is found that adding happiness indicators results in a gain in efficiency. Abou-Zeid and Ben-Akiva (2012) provide a framework to apply this approach to enhance the specification of activity-based models.

This section presented a review of enhancements to activity-based models in five key directions, including: (1) modeling intra-household interactions and joint activity participation, (2) modeling time use and budgeting to account for limited resource availability, (3) modeling multi-day activity schedules, (4) modeling activity planning, and (5) incorporation of well-being indicators to enhance the econometric specification. The next section reviews a behavioral extension to activity-based modeling approach, which focuses on modeling the motivation for activity participation.

2.4 Needs-based Approach

A key weakeness of the operational activity-based models, particularly the day activity schedule approach, is in the specification of activity generation (or pattern-level) models. Existing activity pattern models are specified as utility-maximizing econometric models based on empirical considerations (see Abou-Zeid and Ben-Akiva, 2012). For example, the day activity schedule approach creates a choice set of activity pattern alternatives based on observed data. The model is specified and estimated with various socio-economic variables, and a best model specification is chosen based on statistical significance. A key weakness is in the choice set generation and the model, which is not founded in a behavioral theory that explains individuals' activity choices. While models concering time use provide a basic framework to explain how individuals trade off different activities given a time budget, they do not explicitly model the drivers of activities. This section deals with recent advances in the area of activity-based modeling that deal with explaining activity choices based on a behavioral theory, namely the theory of needs.

As early as the 1970's, Chapin (1974) argued that an individual's activity participation is driven by basic human desires, such as survival, social encounters and ego gratification, drawing from the theory of human motivation as proposed by Maslow (1943). More recently, several other studies including Bowman and Ben-Akiva (2001) also argued that activity demand is also moderated by various factors including, for example, commitments, capabilities and health. Several studies have discussed the relationship between activity participation and human need-satisfaction qualitatively, and few studies have attempted to model this relationship analytically. This section is organized as follows. First, a review of the theory of needs and human motivation is presented. Following this, a review of literature from transportation and behavioral research is presented that discusses the relationship between needs and activities. Then, recently developed analytical studies that provide a framework for a needs-based model are reviewed. Finally, the contribution of this thesis is presented in the context of the state of the art.

2.4.1 Theory of Needs and Human Motivation

Abraham Maslow's seminal paper entitled "A theory of human motivation", provides a framework to understand human actions (see Maslow, 1943). According to this theory, individuals perform actions (activities) only as a means to satisfy end goals. To this end, he classifies the end goals, called needs, into the following five categories: (1) physiological, (2) safety, (3) love/belonging, (4) esteem, and (5) self-actualization (see Figure 2.1, commonly known as Maslow's pyramid or hierarchy of needs). He explains the four bottom needs as deficit needs (D-needs), which may be viewed as obstacles in the way of individuals on the path to engage in the top level need of self-actualization, also known as benefit need (B-need). In his theory, an individual satisfies his/her B-need only after all the D-needs are satisfied.

An important extension of this theory that is relevant in the context of this thesis was provided by Alferder (1972) in a theory called the Existence, Relatedness and Growth (ERG). He reclassified Maslow's physiological and safety needs as "existence", love/belonging as "relatedness", and esteem and self-actualization as "growth". In addition, he hypothesized that these needs coexist for the same individual at the same time, and identified a transition process between them. The coexistence of needs, as theorized by ERG, provides a framework to model multiple needs of an individual, as satisfied by conducting multiple activities.

Another behavioral theory that has received attention in the area of transportation was provided by Selye (1975). In this theory, Selye defines "stress" as a response to a "stressor"

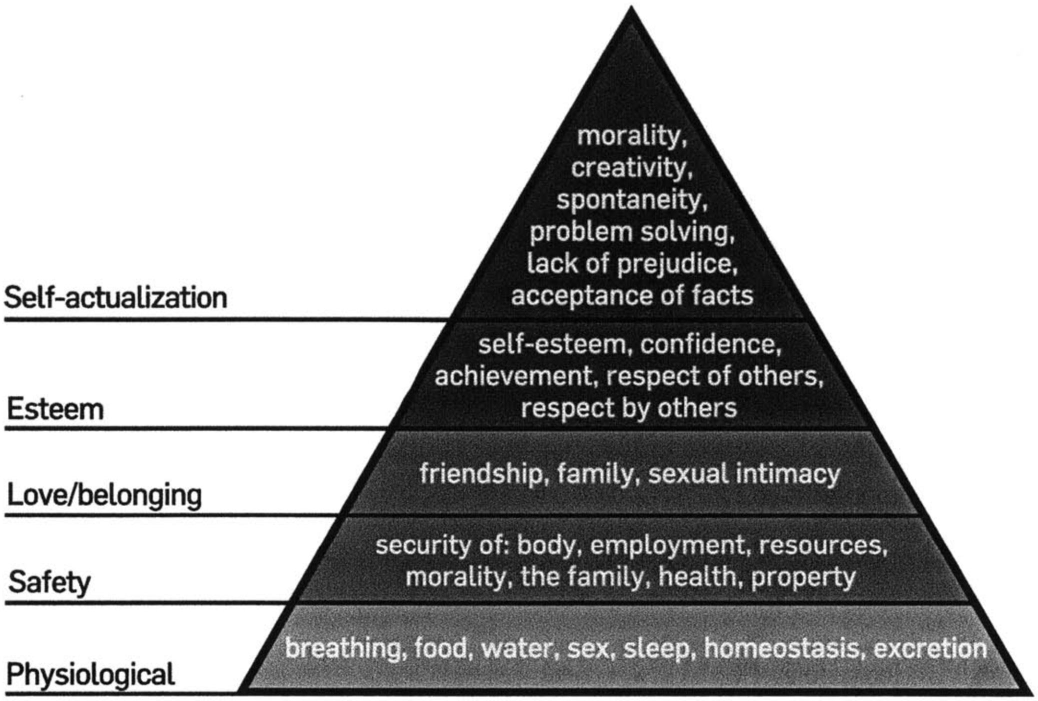

Figure 2.1: Maslow's hierarchy of needs (Maslow, 1943)

which acts as a stimulus. In this theory, he classifies stress reactions into (1) Eustress that motivates and enhances physical and psychological reactions, and (2) Distress that is not resolved through coping or adaptaion, which may lead to anxiety and regression. The two types of stress may coexist and drive individuals to conduct different types of activities.

In the context of activity-based models, it is important to understand from these theories of human motivation or needs that activities are conducted to satisfy needs. While activities are conducted by individuals and are observed, needs are latent and are not explicitly observed. An activity may satisfy several needs. For example, going out for dinner with friends satisfies both physiological/existence need for food and love/belonging/relatedness need for friendship. Conversely, a need may be satisfied by several activities. For example, the physiological need for food may be satisfied by eating at home, or at a restaurant, with friends/family or alone.

Individuals satisfy their needs by conducting different activities periodically. When they do not conduct activities that satisfy a particular need for a period of time, the need builds up. Their choice of activities to be conducted is motivated by their desire to satisfy this, and other unmet needs. However, their ability to conduct activities is restricted by limited availability of resources such as time, money, etc. Evidence from the marketing literature is relevant in this context. For example, Ariely (2008) explains, based on empirical evidence, that individuals' happiness (which is directly related to their satisfaction of needs) is higher when they conduct activities (referring to purchasing behavior) intermittently, so that their needs are constantly satisfied. Conversely, if they conducted the activities occasionally with longer gaps between successive episodes, their level of happiness (need-satisfaction) decreases considerably by the time the activity is conducted again, thereby affecting their overall state of happiness (see, for related literature, Kahneman et al. (1993); Ariely and Loewenstein (2000)).

Based on the theory of needs and human motivation, a framework to model activity generation may be developed as shown in Figure 2.2. According to this figure, travel demand (mobility) is derived from the demand for activities; this forms the basis for activity-based approaches. This framework is extended by explaining activity demand as motivated by needs. Given this framework, literature in the area of needs-based approaches to activity generation is reviewed in the next section.

2.4.2 Needs in Activity-based Approaches

Several studies in the travel demand analysis literature have discussed that activities are conducted to satisfy needs. Most of these are conceptual, rule-based, or generally do not develop the needs-activity relationships into an analytical model (see, for example, Westelius, 1972; Adler and Ben-Akiva, 1979; Nijland et al., 2010; Märki et al., 2011).

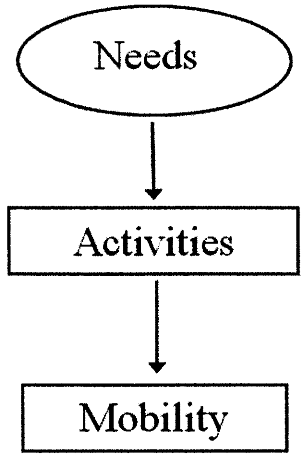

Figure 2.2: Needs as motivators of human activites

Two significant attempts at modeling needs as drivers of activities are discussed here. The first, by Meister et al. (2005), implemented needs into an operational model of activity scheduling. The second, by Arentze et al. (2009b), developed an analytical utility-maximizing framework for needs-based activity generation in both single-day and multi-day contexts.

In the context of an activity scheduler used with a dynamic traffic simulation tool, Meister et al. (2005) operationalize the idea of needs and stress. In this model, activities are modeled to increase an individual's level of utility. Conversely, travel is modeled as causing disutility (unless other activities are conducted during travel, which is currently not modeled in the framework). Therefore, when a decision to conduct an activity is made (i.e. an activity is chosen to be conducted and scheduled), the difference in utility before and after conducting the activity is evaluated, and the alternative that provides the maximum increase (or minimum decrease in case of travel) is chosen. The model also accounts for satiation effect, by modeling decreasing marginal utility with increasing activity duration. While this framework is attractive, the choice of feasible activities is determined empirically based on rules. Moreover, the framework focuses on the scheduling decision and pays little attention to activity generation.

The second set of studies formulate a needs-based utility maximizing model of activity choices. Drawing from inventory theory used in the supply chain management literature, Arentze et al. (2009b) implement a model whereby an individual's need-satisfaction varies with time. Every time the individual conducts an activity, the inventory is replenished (need is satisfied), while the need builds up if the activity is not conducted for a period of time. A utility maximizing model is formulated, where at any point in time an activity is chosen if the amount of utility (inventory) generated by conducting the activity exceeds a certain threshold. The threshold is also considered to be time varying, to account for day-of-week variation, and to account for the fact that thresholds are expected to be higher if the activity was conducted recently and lower if the activity was conducted long ago. A Bayesian estimation procedure is proposed to estimate the model since it is set in a dynamic context. However, this formulation requires information about the last time the activity was conducted by the individual. Since conventional travel surveys collect data on a single week day, the last time an activity was conducted is determined using a random draw to estimate the model (Arentze et al., 2011). Alternatively, a multi day travel survey is proposed to collect more information about the frequency at which activities are conducted (Nijland et al., 2010, 2012).

Nijland et al. (2011) also extend the framework to model interaction between multiple activities. They model the trade-off between multiple activities. To do so, the utility function contains interaction terms between different activities. The model explicitly accounts for the increase or decrease in the need for one activity by conducting another activity. A Bayesian estimation procedure is adopted similar to the single activity model described earlier, which requires information about the last time an activity was conducted.

The notion that activity choices are driven by a desire to maximize need-satisfaction has also been used to model the quality of urban environments. In urban planning research, the quality of urban environment is determined by studying the activities an individual conducts. The hypothesis is that the choice of activities is limited by the availability of opportunities to conduct activities, and therefore by constructing time-space prisms based on individuals' observed activity choices, the quality of the urban environment can be inferred. Arentze et al. (2009a) adopted a needs-based approach to enhance the measurement of the quality of urban environments. In this study, the extent to which individuals' needs are satisfied is measured based on the various dimensions of the activities they conducted. The study reports that greater sensitivity of activity choices to changes in the urban environment is predicted by the needs-based approach as against conventional techniques.

In summary, while these studies are the best known needs-based analytical models formulated, they are limited in their applicability due to the data requirements to estimate the models or due to the assumption they make about the last time an activity was conducted. An objective of this thesis is to develop needs-based models in a stationary context that do not require information about the last time individuals conducted activities before the observed day.

2.5 Conclusion

This chapter presented a review of literature in the area of travel demand analysis and behavioral modeling, including recent advances from behavioral theories. The evolution of disaggregate models was discussed to trace the development of activity-based approaches to travel demand analysis. Operational activity-based models were reviewed to present the state of the practice in activity-based modeling. Recent advances in activity-based modeling were discussed to identify gaps in research. Specifically, the need for behaviorally enhanced activity generation models was identified. The theory of human motivation and needs was reviewed to provide a behavioral framework to describe human activity choices. Studies in the transportation literature that have described needs-based approaches and have implemented needs-based models in activity-based model frameworks were also reviewed. Finally, shortcomings of the existing needs-based analytical models were discussed to motivate the objectives of this thesis.

3 Needs-based Model Framework and Formulation

This chapter develops a conceptual modeling framework of a needs-based approach to activity generation. Section 3.1 develops a conceptual relationship between need-satisfaction and activity participation and defines the terminology used in the analytical model that follows. Section 3.1.2 formulates a conceptual model for the general case of multiple needs and activities. Following this, an analytical optimization model to describe the choice of activity location, duration, expenditure, and frequency is formulated in Section 3.2. Section 3.3 describes the solution procedure and properties of the solution. Section 3.4 concludes the chapter.

3.1 Needs-based Approach

This section develops a conceptual relationship between need-satisfaction and activity generation, drawing from and improving upon the literature described in Chapter 2. Section 3.1.1 defines the terms used in the framework and the analytical formualtion. Following this, Section 3.1.2 defines the problem to be addressed and sets up an optimization framework to address this problem. A special case of this general framework for a single need - single activity model is formulated and solved in the remaining sections of this chapter.

3.1.1 Definitions

1. **Needs:** According to the theory of needs (Maslow, 1943; Chapin, 1974), human activities are motivated by a set of different and distinct needs. There is a finite set of needs that motivate all human activities, and these needs coexist. A need may be satisfied by several activities, and conversely, an activity may satisfy several needs. Needs are unobserved or latent; only the activities that satisfy the needs are observed.

2. **Psychological Inventory:** We associate a need with a "psychological inventory", denoted as I, which can be interpreted as the level of need-satisfaction at a certain point in time (see Figure 3.1). When the need is low, the psychological inventory is high and vice versa. Over time, the need builds up and so the inventory gets depleted. The inventory is replenished when the individual performs an activity that satisfies the need. In other words, the level of psychological inventory corresponds to the level of satisfaction of the needs. A gain in the psychological inventory of a need may be viewed as being similar to the utility gained by performing activities that satisfy this need. In Figure 3.1, the individual conducts an activity that satisfies the need at times T_1, T_2, T_3 and T_4 to replenish the inventory. Between these times, the inventory is consumed as the need builds up.

3. **Activity Production:** The quantity of psychological inventory generated by performing an activity is referred to as the activity production and denoted as Q. It is a non-negative function of the various inputs that are expended to perform the activity, namely, activity duration T_a, activity expenditure C_a, and activity location attractiveness A, where a denotes an activity. Attractiveness is measured by how attractive a location is for the activity being modeled. For example, to model shopping activity production, measures of attractiveness may include retail employment density, retail area, etc. Mathematically, the activity production Q is calculated using the activity production function, denoted as $q(T_a, C_a, A)$. In Figure 3.1, the individual conducts the activity with varying levels of inputs (duration, expenditure, and attractiveness) at

times T_1, T_2, T_3 and T_4 to generate Q_1, Q_2, Q_3 and Q_4 units of inventory respectively. The following properties are desired for the activity production function:

a) Monotonicity: With a monotonic production function, the extent to which an individual's psychological inventory is replenished by performing an activity is greater when more time or money is spent performing the activity, or when it is performed at a more attractive location (e.g. shopping at a location with larger retail space). Mathematically, this condition is written as $\frac{dq(T_a,C_a,A)}{dT_a} > 0$, $\frac{dq(T_a,C_a,A)}{dC_a} > 0$ and $\frac{dq(T_a,C_a,A)}{dA} > 0$.

b) Concavity: A concave activity production function has the property of decreasing marginal returns with respect to inputs. Consequently, the additional benefit (inventory) gained from utilizing extra resources (time, money, attractiveness) to perform the activity is decreasing. This property captures satiation in activity production. Mathematically, this condition is written as $\frac{d^2q(T_a,C_a,A)}{dT_a^2} < 0$, $\frac{d^2q(T_a,C_a,A)}{dC_a^2} < 0$ and $\frac{d^2q(T_a,C_a,A)}{dA^2} < 0$.

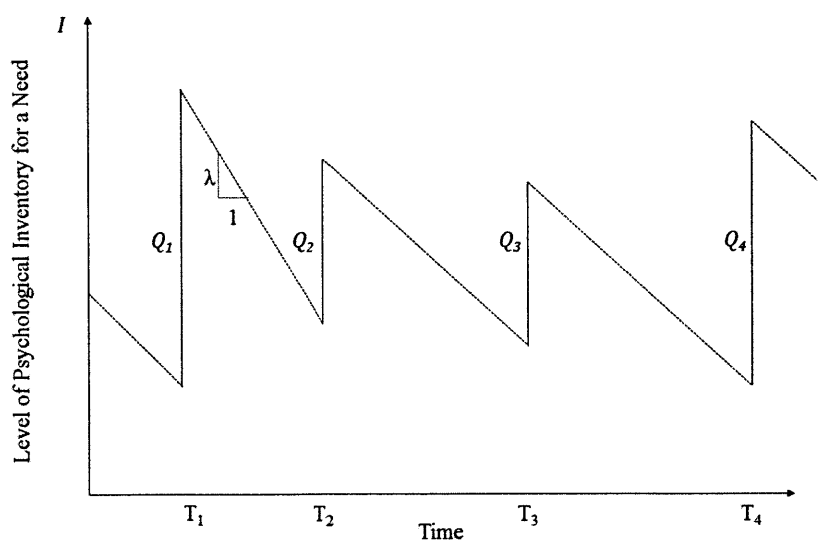

Figure 3.1: Evolution of psychological inventory of a need over time

3.1.2 Formulation

3.1.2.1 Problem Formulation

Given an individual with known socio-economic characteristics and fixed mobility status (e.g. residential location, vehicle ownership), the problem to be addressed is how the individual chooses the location, duration, expenditure, and frequency of activities to be performed such that his/her need-satisfaction over time is maximized. While some activities are rigid (e.g. work, school, picking up a child from daycare) and need to be performed at fixed locations with fixed durations, expenditures, and frequencies, other activities are flexible (e.g. shopping, recreation). However, the choice of location, duration, expenditure, and frequency available for performing these flexible activities is constrained by the amount of time and money available after allocating these resources to the rigid activities.

3.1.2.2 Optimization Framework

The individual chooses his/her activity dimensions, including activity frequency, sequence, locations, durations, and expenditure for all the activities the individual performs such that his/her need-satisfaction is maximized over time. For every need that the individual seeks to satisfy, his/her need-satisfaction is measured by a psychological inventory with respect to that need. The optimization problem maximizes a function of the vector of psychological inventories with respect to all the needs an individual wishes to satisfy. The choices are subject to time and monetary budget constraints, that account for limited availability of time and income. Additionally, the problem can impose constraints on the level of inventory that can be reached by an individual, to reflect satiation and the need to maintain a minimum safety stock.

3.2 Single Need Single Activity Model

This section develops an analytical model of activity choices for a single need and the activity that satisfies the need. In reality, individuals conduct several activities to satisfy several needs. However, in the simplistic model developed here, the various needs and activities are treated as independent. Using this framework, the decision for every activity an individual conducts is modeled independently as an optimization model that maximizes the need-satisfaction resulting from the activity.

3.2.1 Assumptions

The following simplifying assumptions are employed in formulating the model.

1. Single need and single activity: The model considers one need and the activity that satisfies this need. The need is satisfied only by this activity, and conversely the activity satisfies only this need. Chapter 5 provides a conceptual framework to extend the model developed in this chapter to multiple needs and activities.

2. Constant rate of depletion: The level of psychological inventory depletes at a constant rate λ, which may vary across individuals. A relaxation of this assumption is discussed in Chapter 5.

3. Steady-state conditions: The model is formulated for steady-state conditions wherein an individual performs the activity at a fixed location i for a fixed duration T_a and spends a fixed amount of money C_a at constant intervals of time. In Firgure 3.2, which illustrates the evolution of the psychological inventory of a need over time, the individual conducts the activity at regular intervals at times T_1, T_2, T_3, etc. with the same level of activity production Q each time the activity is conducted. Clearly, in reality individuals do not conduct activities at regular intervals, at the same location, for the same duration and spend fixed amounts of money. However, travel surveys usually collect data on a random weekday. Therefore, this steady-state model does

not capture the short term dynamic activity choices, but instead describes long term stationary patterns to predict the probability of an individual conducting an activity on a random weekday. Chapter 5 discusses a framework to extend the model developed in this chapter to a dynamic model.

4. Minimum cycle time: The activity is performed at most once in a day. Consequently, the cycle time for the activity, defined as the time between successive performances of the activity, is at least one day. It can be seen from Figure 3.2 that the cycle time is given by $\frac{Q}{\lambda}$. The average frequency is the inverse of the cycle time, i.e. $\frac{\lambda}{Q}$.

5. Minimum and maximum levels of psychological inventory: The individual performs the activity when the level of the psychological inventory drops to a minimum threshold value denoted as I_{min}, which can be interpreted as a safety stock for the need. The maximum level of inventory that the individual can attain by performing an activity is limited to I_{sat}, the satiation limit, beyond which it is not possible for the individual to increase his/her level of inventory. It is assumed that the maximum level of inventory is a characteristic of the individual since it reflects satiation, while the minimum level of inventory is a decision that the individual makes (i.e. when to "restock").

3.2.2 Mathematical Formulation

The individual chooses a location i, activity duration T_a, activity expenditure C_a, activity frequency, and a minimum level of inventory to be maintained I_{min} for performing the activity such that the individual's need-satisfaction, measured by the average level of psychological inventory over time I_{avg} (see Figure 3.2), is maximized over time. The maximum level of inventory attained by an individual by conducting an activity is limited to I_{sat}. It is clear that the variation in the inventory over time, and not just the average level over time, also affects the individual's need-satisfaction and activity choices (see, for example, evidence from the psychology literature reported in Kahneman et al., 1993; Ariely and Loewenstein, 2000; Redelmeier et al., 2003). However, under the steady state assumption, the proposed

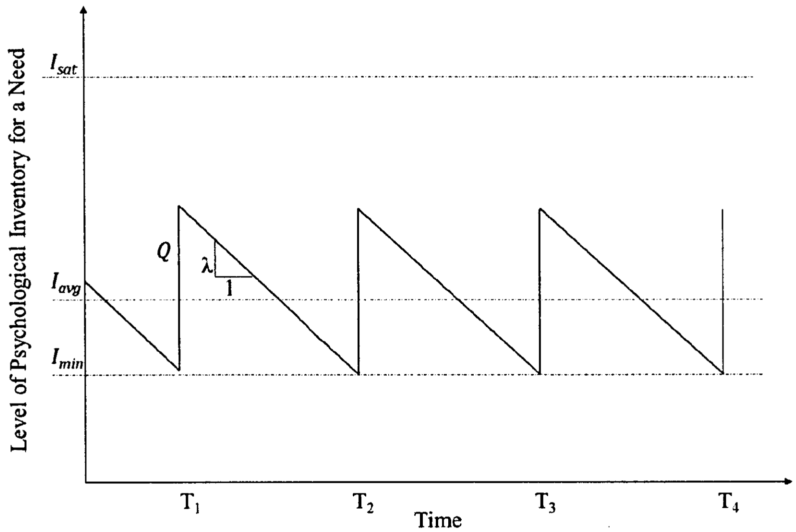

Figure 3.2: Psychological inventory of a need over time under steady-state conditions

formulation is equivalent to a model that maximizes the minimium level of inventory, since the maximum level (I_{sat}) of inventory is fixed (and is reached under the steady state formulation, see Section 3.3.1) and the minimum level (I_{min}) is a decision variable. Therefore, this model accounts for the variation in the inventory over time by fixing the maximum level as a characteristic, selecting the minimum level as a decision variable, and maximizing the average level of inventory over time under steady state conditions. In addition, the individual's choices are also subject to time and monetary budget constraints. Let TT_i and TC_i denote the travel time and travel cost, respectively, associated with performing the activity at location i. The optimization model is formulated as follows for a given individual:

$$\underset{i, T_a, C_a, I_{min}}{Maximize} \quad I_{avg} = I_{min} + \frac{1}{2}Q_i \tag{3.1}$$

Subject to:

$$Q_i = q(T_a - T_0, C_a, A_i) \tag{3.2}$$

$$T_a + TT_i \leq t(\frac{Q_i}{\lambda}) \tag{3.3}$$

$$C_a + TC_i \leq c(\frac{Q_i}{\lambda}) \tag{3.4}$$

$$I_{min} + Q_i \leq I_{sat} \tag{3.5}$$

Constraint (3.2) expresses the activity production Q_i at a location i as a function of the inputs that are invested in conducting the activity. These include the effective activity duration ($T_a - T_0$), expenditure (C_a) and location attractiveness (A_i). The effective duration that produces psychological inventory is less than the actual amount of time spent conducting the activity by a quantity T_0, referred to as the set-up time. T_0, a psychological characteristic of an individual, accounts for the inefficiency involved with starting up the activity each time it is conducted, and may be viewed as the minimum time an individual must invest in conducting the activity each time before any inventory is generated. For a shopping activity, this may include the time spent on billing, walking from and to the parking lot, etc., which do not contribute to the actual shopping activity production but are necessary to conduct the activity. Constraints (3.3) and (3.4) ensure that the total amount of time and money that the individual spends on performing the activity per cycle are at most equal to the amount of time and money available for this activity, given that the individual has made decisions about all other activities. Note that the amount of time and money available depends on the cycle time ($\frac{Q_i}{\lambda}$), given the quantity of time (t) and income (c) available (per unit time) for this activity. Therefore, if the activity is performed less frequently, the amount of time and money available per cycle is higher (since the cycle time is higher). Conversely, if the activity is performed more frequently (with a lower cycle time), less time and money are available to perform the activity per cycle. Constraint (3.5) ensures that the replenished level of inventory after the activity is performed does not exceed the satiation limit for the individual.

The needs-based model formulated in this section for out-of-home activities that require travel may also be extended to model in-home activities. For example, online shopping may be modeled by considering it as an alternative in the location choice set. Its attractiveness may be modeled using a dummy variable (replacing attractiveness A_i in the activity production function). whose coefficient can be estimated empirically. While no out-of-home travel is involved and hence travel time and travel cost are zero, activity set-up time prevents the individual from conducting the activity too frequently.

3.3 Solution Procedure and Properties

This section describes a procedure to solve the optimization problem formulated in Section 3.2.2. The problem is solved using a two stage optimization process described in Section 3.3.1. The properties of the resulting solution are discussed in Section 3.3.2.1. Finally, a flexible translog form is considered for the activity production function to study the solution properties in greater detail in Section 3.3.2.2.

3.3.1 Solution Procedure

For mathematical simplicity, we assume that the budget constraint (3.4) is not binding. In reality, time is more often a binding constraint that affects the choice of activities and therefore the simplification has little effect on the behavioral realism of the model. Therefore, the decision on activity expenditure and the corresponding budget constraint are ignored hereafter. A simplistic treatment of the cost budget constraint, without ignoring it completely, is to incorporate it in the generation of location choice alternatives based on a weekly budget and expected expenditure at different locations. Since the optimization problem has discrete (location) and continuous (duration, frequency, and minimum level of inventory) decision variables, a solution may be obtained in two stages. First, conditional upon a location i (and thus given TT_i and A_i), the optimal value $\widetilde{T}_{ai}$ of activity duration T_a for each location i

that maximizes the objective function ($I_{avg,i} = I_{min} + \frac{1}{2}Q_i$) is computed. Thus, the optimal values of the activity production, $\tilde{Q}_i$, and the average level of inventory at each location ($\widetilde{I}_{avg,i} = I_{min} + \frac{1}{2}\tilde{Q}_i$) can be computed. The optimal frequency of performing the activity at this location is given by $\frac{\lambda}{\tilde{Q}_i}$. In the second stage, the location i that has the highest value of $\widetilde{I}_{avg,i}$ is found to be the optimal location.

3.3.1.1 First Stage Optimization Model

The first stage optimization model at a given location i can be formulated as follows:

$$\underset{T_a, I_{min}}{Maximize} \quad I_{avg,i} = \quad I_{min} + \frac{1}{2}Q_i \tag{3.6}$$

Subject to:

$$Q_i = q(T_a - T_0, A_i) \tag{3.7}$$

$$T_a + TT_i \leq t(\frac{Q_i}{\lambda}) \tag{3.8}$$

$$I_{min} + Q_i \leq I_{sat} \tag{3.9}$$

The Lagrangian function can be written as follows, with Q_i defined by Equation (3.7):

$$L_i = I_{min} + \frac{1}{2}Q_i + \mu_1(T_a + TT_i - t(\frac{Q_i}{\lambda})) + \mu_2(I_{min} + Q_i - I_{sat}) \tag{3.10}$$

In Equation (3.10), μ_1 and μ_2 are the Lagrangian multipliers of the time and inventory constraints, respectively. The optimization problem can be solved by writing the first order conditions of the Lagrangian, along with the Kuhn-Tucker conditions for the constraints. The inventory constraint (3.9) becomes an equality on applying the first order condition to the decision variable I_{min}. The first order condition, along with the corresponding Kuhn-Tucker condition, is written as follows:

$$\frac{dL_i}{dI_{min}} = 1 + \mu_2 = 0 \Rightarrow \mu_2 = -1 \tag{3.11}$$

$$\mu_2(I_{min} + Q_i - I_{sat}) = 0 \; ; \; \mu_2 < 0 \Rightarrow I_{min} = I_{sat} - Q_i \tag{3.12}$$

We may substitute the value of I_{min} obtained in Equation (3.12) in Equation (3.6) to formulate the optimization problem with the objective as shown below with constraints (3.7) and (3.8):

$$\underset{T_a}{Maximize} \quad I_{avg,i} = \; I_{sat} - \frac{1}{2}Q_i \tag{3.13}$$

This new formulation requires Q_i to be minimized, in order to maximize $I_{avg,i}$. Intuitively, this new model may be interpreted as trying to minimize the depletion from the maximum level of inventory (I_{sat}), thereby maximizing the average level of satisfaction, subject to a time constraint (3.8). The Lagrangian can now be expressed as:

$$L_i = I_{sat} - \frac{1}{2}Q_i + \mu_1(T_a + TT_i - t(\frac{Q_i}{\lambda})) \tag{3.14}$$

As noted earlier, the activity production at any location is a function of the duration and location attractiveness ($Q_i = q(T_a - T_0, A_i)$). To find the optimal value of T_a at location i, the first order condition in T_a is written as:

$$\frac{dL_i}{dT_a} = -\frac{dq(T_a - T_0, A_i)}{dT_a}(\frac{1}{2} + \mu_1\frac{t}{\lambda}) + \mu_1 = 0 \tag{3.15}$$

The Kuhn-Tucker condition for the time constraint is written as:

$$\mu_1(T_a + TT_i - t(\frac{q(T_a - T_0, A_i)}{\lambda})) = 0 \; ; \; \mu_1 \leq 0 \tag{3.16}$$

Equation (3.16) may be satisfied when either $\mu_1 = 0$ or the time constraint is an equality. Each of these cases is considered separately, and the optimal solution to the first stage optimization problem is obtained.

Case 1: Constraint is not binding and $\mu_1 = 0$ Substituting $\mu_1 = 0$ in the first order condition, Equation (3.15), the value of optimal activity duration at location i, denoted by $\widetilde{T}_{ai}$, is computed by solving the following equation:

$$\frac{dq(T_a - T_0, A_i)}{dT_a} \mid_{\widetilde{T}_{ai}} = 0 \tag{3.17}$$

The value of duration obtained by solving Equation (3.17) is optimal if the time constraint for this value of $\widetilde{T}_{ai}$ is satisfied, and the second order condition of L_i is satisfied as:

$$\frac{d^2L_i}{dT_a^2} = -[\frac{d^2q(T_a - T_0, A_i)}{dT_a^2}(\frac{1}{2})] \mid_{\widetilde{T}_{ai}} < 0 \tag{3.18}$$

Equation (3.18) can only be satisfied if $\frac{d^2q(T_a - T_0, A_i)}{dT_a^2}$ is positive. However, the assumption of concavity of the activity production function with respect to inputs requires the second derivative (total, not partial) to be negative. Therefore, a solution to this case would maximize Q_i, and consequently minimize L_i. However, a maximum of the objective function is obtained when L_i is maximized, and hence, since the solution to this case minimizes the objective function, it is rejected.

Case 2: Constraint is binding and $\mu_1 < 0$ In this case, the time constraint is an equality and is an equation with a single unknown variable. In other words, the value of duration ($\widetilde{T}_{ai}$) that maximizes L_i and the objective function $I_{avg,i}$ at location i is found by solving the following equation, where the slack in the time constraint for a duration T_a is referred to as $s(T_a)$:

$$s(\widetilde{T}_{ai}) = \widetilde{T}_{ai} + TT_i - t(\frac{q(\widetilde{T}_{ai} - T_0, A_i)}{\lambda}) = 0 \tag{3.19}$$

For a general function $q(T_a - T_0, A_i)$, this equation is transcendental and does not have a closed form solution for the duration. However, knowing that the production function is non-negative, monotonic, and concave in T_a, the generic shape of $s(T_a)$, given the travel time, attractiveness, time availability and the function q, is as shown in Figure 3.3, which also illustrates the variation of activity production as a function of activity duration. Note that depending on the values of the parameters in the constraint equation, the $s(T_a)$ curve may always be increasing (i.e. if $\frac{ds(T_a)}{dT_a} > 0 \; \forall \; T_a \geq 0$). However, this case is not illustrated since it always corresponds to infeasibility of the constraint equation (i.e. $s(T_a = T_0) > 0, \frac{ds(T_a)}{dT_a} > 0 \; \forall \; T_a \geq T_0 \Rightarrow s(T_a) > 0 \; \forall \; T_a \geq T_0$). Depending on the values of the various parameters in

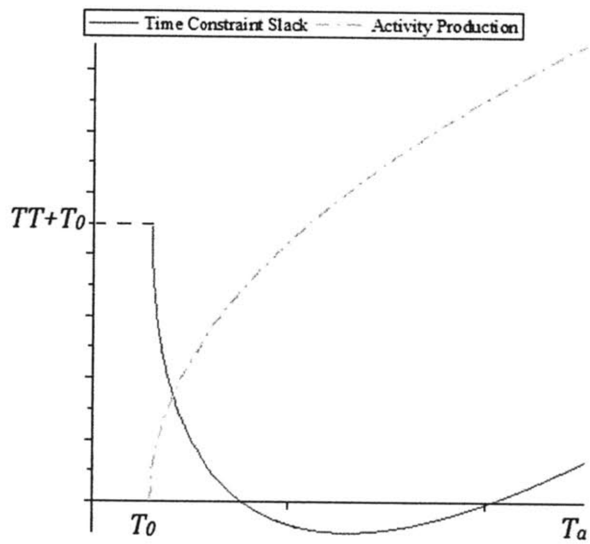

Figure 3.3: Variation of activity production and the constraint slack with respect to activity duration

the constraint equation, the actual slack curve may be either shifted upward or downward from the one shown in Figure 3.3. Consequently, the constraint equation may have two solutions (as shown in the figure, or when the slack curve shifts down), one solution (when the slack curve shifts slightly upward), or no solution (when the slack curve shifts further upward). In each of these cases, the following procedure is used to select the optimal solution:

1. Two Solutions: In this case, the value of the objective function $I_{avg,i}$ is computed at both solutions and the solution that maximizes $I_{avg,i}$ is accepted as the optimal solution. Since maximizing $I_{avg,i}$ corresponds to minimizing Q_i at location i, and since q is a monotonically increasing function of T_a, the solution that is selected is one that has a smaller value of T_a. Behaviorally, this indicates that by performing an activity for a shorter duration of time more frequently, an individual maintains a higher average level of need-satisfaction since the depletion from the satiation limit is minimized.

2. One Solution: In case the constraint equation is satisfied as an equality at exactly one value of duration, then this value is accepted as the optimal duration.

3. No Solution: When the constraint slack is always positive, the constraint equation does not have a solution. Given limited availability of time (t) and the inventory consumption rate (λ), there are two situations that lead to infeasibility of the time constraint. First, if a location is far off (very high TT_i), the total time spent on conducting the activity (i.e., the sum of activity duration and travel time) is high, and is likely to exceed the time available per cycle. Second, when a location i has very low attractiveness (A_i), the activity production (Q_i) at this location is low, and the cycle time ($\frac{Q_i}{\lambda}$) for conducting an activity at this location is also low. Consequently, the time available to conduct the activity at this location during one cycle ($t(\frac{Q_i}{\lambda})$) is low, and so time available to conduct the activity at this location is likely to be lower than the time required to conduct the activity at this location. Therefore, locations which do not have a real solution to the constraint equation are considered infeasible, and are eliminated from the choice set for the second stage location choice optimization.

Given the nature of the equation, Brouwer's fixed point theorem may be used to obtain a sufficient condition for the existence of a solution over a range of values of T_a, say $T_a \in (x, y)$. If the constraint slack function $s(T_a)$ has different signs at values x and y, then there is at least one solution to this equation over this range. Mathematically, this may be stated as:

$$s(x)s(y) \leq 0 \Rightarrow \exists\ T_a \in (x, y) \text{ such that } (s(T_a) = 0) \tag{3.20}$$

It must be noted, however, that this is not a necessary condition and its ability to discover a solution is sensitive to the length of the search interval.

At the end of the first stage optimization, the feasibility of every location is determined. Further, for all feasible locations, the optimal solution may be computed as:

1. Duration ($\widetilde{T}_{ai}$) that satisfies the constraint: $\widetilde{T}_{ai} + TT_i - t(\frac{q(\widetilde{T}_{ai} - T_0, A_i)}{\lambda}) = 0$
2. Activity production ($\widetilde{Q}_i$) , knowing the activity duration: $\widetilde{Q}_i = q(\widetilde{T}_{ai} - T_0, A_i)$
3. Frequency ($\widetilde{f}_i$) defined as the inverse of the cycle time: $\widetilde{f}_i = \frac{\lambda}{Q_i}$
4. Average level of inventory ($\widetilde{I}_{avg,i}$), knowing the activity production: $\widetilde{I}_{avg,i} = I_{sat} - \frac{1}{2}\widetilde{Q}_i$

3.3.1.2 Second Stage Optimization Model

The second stage optimization model is a discrete optimization problem that finds the optimal location. Given a set of feasible locations, and the optimal duration, frequency, and average level of inventory to perform the activity at each location, the second stage optimization problem selects the solution that maximizes the level of need-satisfaction across all these locations. Mathematically, this problem may be formulated as:

$$\underset{i}{Maximize} \quad \widetilde{I}_{avg,i} = I_{sat} - \frac{1}{2}\widetilde{Q}_i \tag{3.21}$$

At the end of the second stage optimization, the set of activity dimensions that maximize an individual's level of need-satisfaction or average level of psychological inventory is given by the optimal location (i), duration ($\widetilde{T}_{ai}$), and frequency ($\widetilde{f}_i$). It must be noted that I_{sat} is a psychological characteristic of an individual, which may be estimated empirically, subject to identification normalization.

3.3.2 Solution Properties and the Activity Production Function

In this section, the behavioral properties that are supported by, and desired of this model are presented. A translog form for the activity production function is verified to support the desired properties.

3.3.2.1 Solution Properties

Three behavioral properties of the optimal solution are discussed in this section. While the first property follows from the mathematical derivations presented in Section 3.3.1, the second and third properties are desirable. The mathematical conditions desired of the optimal solution are presented here.

Property 1: Resource constraints dictate activity choices

The optimal solution is one where the peak of the psychological inventory saw-tooth reaches I_{sat}. This follows from Equation (3.12) and may be visualized as shown in Figure 3.4. At optimality, an individual chooses to maintain a high level of need-satisfaction by minimizing the depletion from I_{sat} before performing the activity each time. While theoretically this could be achieved by performing the activity continuously in very small quantities, this is not possible due to limited availability of time. Thus, the solution is in line with behavioral expectation that resource (time, money) constraints limit the level of need-satisfaction that can be achieved and necessitate an individual to perform activities at discrete intervals of time.

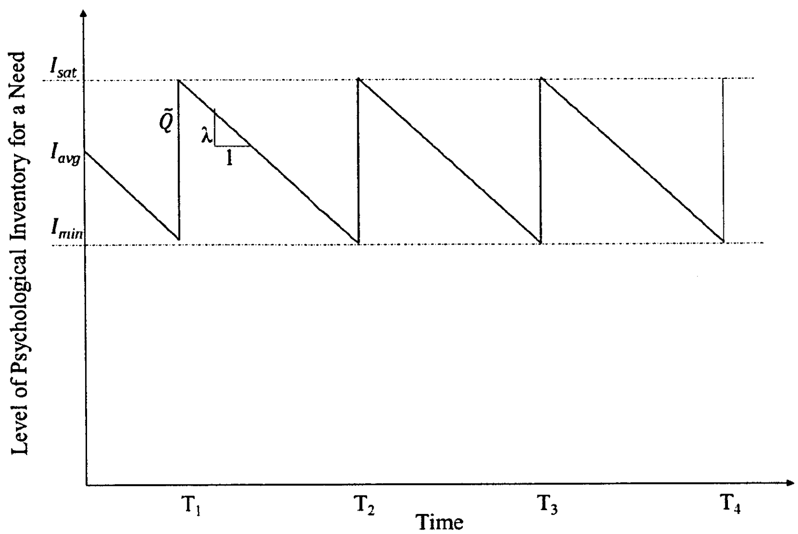

Figure 3.4: Optimal variation of the psychological inventory of a need over time under steady-state conditions

Property 2: Given equal travel times, a more attractive location is preferred

Given two locations with the same travel time (TT), we expect that an individual will choose a location with higher attractiveness. Mathematically, this requires the optimal average level of inventory at the more attractive location to be higher. Based on Equation (3.13), this requires the more attractive location to have a lower value of optimal activity production. Further, since the activity production function is monotonically increasing in the activity duration, this property is satisfied when the more attractive location has a lower value of optimal activity duration ($\widetilde{T_a}$). Mathematically, this property may be stated as satisfy the property $\frac{d\widetilde{T_a}}{dA} < 0$. Differentiating Equation (3.19), we obtain the following simplified condition:

$$\frac{d}{dA}(\widetilde{T_a} + TT - t(\frac{\widetilde{Q}}{\lambda})) = 0 \Rightarrow \frac{d\widetilde{T_a}}{dA} = \frac{\frac{t}{\lambda}\frac{d\widetilde{Q}}{dA}}{1 - \frac{t}{\lambda}\frac{d\widetilde{Q}}{dT_a}} < 0 \tag{3.22}$$

Property 3: Given equal attractiveness, a closer location is preferred

Given two locations with the same attractiveness (A), we expect that an individual will choose a location with lower travel time. Mathematically, this requires the optimal average level of inventory at the closer location to be higher. Based on Equation (3.13), this requires the closer location to have a lower value of optimal activity production. Further, since the activity production function is monotonically increasing in the activity duration, this property is satisfied when the closer location has a lower value of optimal activity duration, or conversely when a location that is farther away has a higher value of optimal activity duration ($\widetilde{T}_a$). Mathematically, this property may be stated as satisfy the property $\frac{d\widetilde{T}_a}{dTT} > 0$. Differentiating Equation (3.19), we obtain:

$$\frac{d}{dTT}(\widetilde{T}_a + TT - t(\frac{\widetilde{Q}}{\lambda})) = 0 \Rightarrow \frac{d\widetilde{T}_a}{dTT} = \frac{1}{\frac{t}{\lambda}\frac{d\widetilde{Q}}{d\widetilde{T}_a} - 1} > 0 \tag{3.23}$$

Properties 2 and 3 described above are desired and satisfied by the solution when Equations (3.22) and (3.23) are satisfied. However, verifying these constraints requires knowledge of the functional form of the activity production to describe the optimal solutions $\widetilde{T}_a$ and $\widetilde{Q}$. Given the transcendental nature of this solution, a specific functional form is chosen here to empirically verify these properties.

3.3.2.2 Translog Form of the Activity Production Function

To verify that the optimal solution satisfies the properties described in the preceding section, it is necessary to choose a functional form for the activity production function. This functional form allows for flexibility in the relationship between Q, T_a, and A (by allowing for flexible substitution and variable elasticity) and ensures that the activity production function is non-negative. The translog functional form, which is a commonly used production function in economic theory, is chosen for the activity production function. The mathematical expression for the translog function is as follows:

$$
\begin{aligned}
Q &= q(T_a - T_0, A) \qquad (3.24)\\
&= exp(q_o + q_1 ln(T_a - T_0) + q_2 ln(A) + q_3 ln(T_a - T_0) ln(A) + q_4 (ln(T_a - T_0))^2 + q_5 (ln(A))^2)
\end{aligned}
$$

The parameters q_0, q_1, q_2, q_3, q_4 and q_5 determine the shape and the elasticity of activity production with respect to the inputs (i.e. effective duration and attractiveness). It may be noted that while it is possible to impose monotonicity and concavity globally to the translog function, this greatly reduces the flexibility of the function (Terrel, 1996). Imposing monotonicity and concavity over the realistic range of values of T_a and A provides a good trade-off between flexibility of the function and the desired properties (see Terrel, 1996, for a procedure to impose monotonicity and concavity over specific ranges of values of the inputs to the translog production function). The realistic range of these variables (e.g. 1 hour to 14 hours for out of home activity durations and 1 to 100 persons per square mile for retail employment density in the locations for shopping activity) can be scaled without loss of generality.

For this function q to be monotonically increasing, the first derivative of the production function with respect to T_a and A should be positive as shown below:

$$
\frac{dQ}{dT_a} = \frac{dq(T_a - T_0, A)}{dT_a} = \frac{1}{T_a - T_0}(q_1 + q_3 ln(A) + 2q_4 ln(T_a - T_0))Q > 0 \qquad (3.25)
$$

$$
\frac{dQ}{dA} = \frac{dq(T_a - T_0, A)}{dA} = \frac{1}{A}(q_2 + q_3 ln(T_a - T_0) + 2q_5 ln(A))Q > 0 \qquad (3.26)
$$

Similarly, for the concavity condition to hold, the second derivative of the production function with respect to T_a and A should be negative as shown below:

$$\begin{aligned}
\frac{d^2Q}{dT_a^2} &= \frac{d^2q(T_a - T_0, A)}{dT_a^2} && (3.27)\\
&= \frac{1}{(T_a - T_0)^2}(-q_1 - q_3ln(A) - 2q_4ln(T_a - T_0) + 2q_4 + (q_1 + q_3ln(A) + 2q_4ln(T_a - T_0))^2)Q < 0 \\
\frac{d^2Q}{dA^2} &= \frac{d^2q(T_a - T_0, A)}{dA^2} && (3.28)\\
&= \frac{1}{A^2}(-q_2 - q_3ln(T_a - T_0) - 2q_5ln(A) + 2q_5 + (q_2 + q_3ln(T_a - T_0) + 2q_5ln(A))^2)Q < 0
\end{aligned}$$

The optimal duration at a location obtained by solving the time constraint (3.19) using a translog production function does not have a closed functional form and is analytically intractable.

Empirical analysis of the optimal solution over a range of values of the parameters of the model verified that Properties 2 and 3 described in Section 3.3.2.1 are satisfied by the optimal solution. Figures 3.5 and 3.6 illustrate the variation of the optimal activity duration as a function of location attractiveness and travel time, respectively. The model parameters used to plot these curves are documented in Section 4.4, which describes a Monte Carlo experiment conducted to test the empirical model developed in Chapter 4. Figure 3.5 indicates that the optimal activity duration decreases with increasing attractiveness (given fixed travel time), which is consistent with Equation (3.22). Similarly, Figure 3.6 indicates that the optimal activity duration increases with increasing travel time (given fixed attractiveness), which is consistent with Equation (3.23).

3.4 Conclusion

This chapter developed a conceptual framework for a needs-based approach to activity generation for travel demand models. The relationship between need-satisfaction and activity participation was explained through the idea of "psychological inventory" and "activity pro-

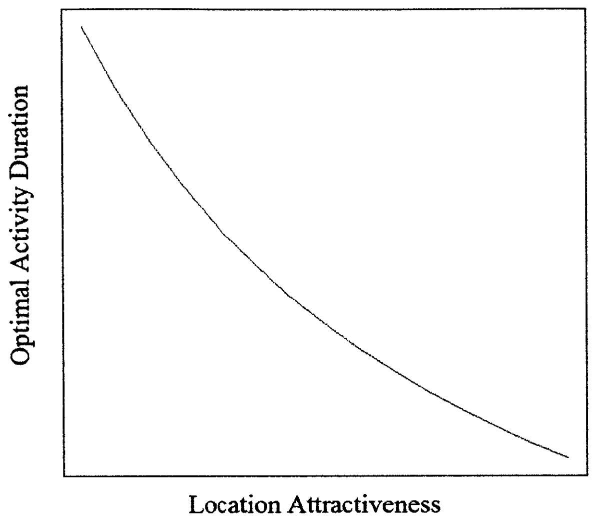

Figure 3.5: Optimal activity duration as a function of location attractiveness

duction". A general framework for an optimization problem to explain the choice of various activity dimensions like frequency, sequence, location, duration, expenditure, etc. was presented. This formulation was developed analytically to describe the choice of activity location, duration, and frequency for the case of a single need and the activity that satisfies the need under steady-state conditions. A two-stage solution procedure was developed, which first solved for the optimal duration and frequency at each location, and then solved for the optimal location that maximizes an individual's need-satisfaction (average level of psychological inventory). The general solution properties were studied and verified to be in line with intuition. Finally, a translog functional form for the activity production function was tested to empirically verify that the expected solution properties are satisfied.

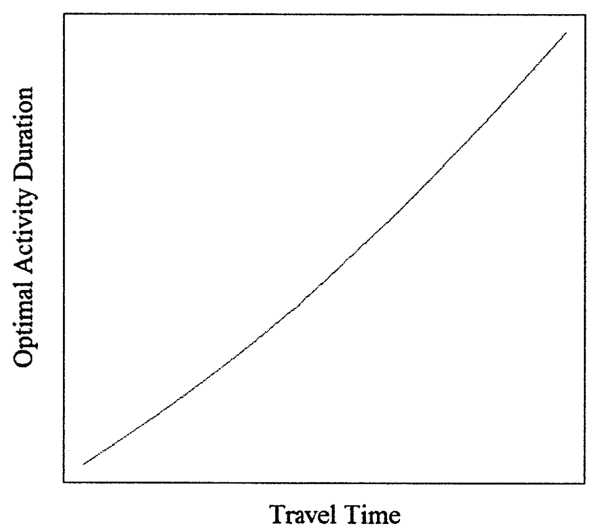

Figure 3.6: Optimal activity duration as a function of travel time

4 Emprical Estimation of Needs-based Model

In this chapter, a method to estimate the needs-based model formulated in Chapter 3 from standard travel diary data is developed. The data available from travel surveys are described in Section 4.1. The empirical model, described in Section 4.2, additionally contains stochasticity to account for the various sources of error and heterogeneity, and accounts for the effect of aggregate representation of location alternatives (e.g. use of Traffic Analysis Zones instead of shopping malls). Section 4.3 develops a maximum likelihood estimator that can be applied to single day travel diary data and requires no knowledge about the last time an activity was conducted. Section 4.4 presents a Monte Carlo experiment conducted to verify that the estimator can recover the true model parameters from observable data. Section 4.5 presents a case study of an empirical model developed for the Denver Metropolitan Area. A model of activity location, duration and frequency choices for shopping conducted as the primary activity of the day is presented. Section 4.6 concludes the chapter.

4.1 Travel Diary Data

In a typical travel survey, respondents record details about the various trips and activities they conducted on a given day. For a single need - single activity needs-based model, information relating to one activity is relevant. For the activity of interest (e.g. shopping), the following data are available for an individual n. First, an indicator δ_n, defined as follows is available:

$$\delta_n = \begin{cases} 1 & \text{if the activity was performed on the observed day} \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

Additionally, for an individual who performed the activity on the observed day, his/her chosen location i_n and chosen duration $T_{obs,n}$ are available. While the activity may be conducted at activity centers (e.g. shopping at a mall), the location i_n is typically available at the resolution of the Traffic Analysis Zone (TAZ) in which the chosen activity center is located. The activity duration is reported in units of time (e.g. hours, minutes).

4.2 Empirical Model

This section presents an empirical model that can be estimated from standard travel diary data. The empirical model captures various sources of stochasticity in the data, including heterogeneity of characteristics and error due to unobserved attributes, measurement errors, optimization errors on the part of the decision-maker, etc. Additionally, it models the effect of using aggregate location alternatives, by including "size variables" in the model. The various sources of stochasticity and the inclusion of size variables are described here.

4.2.1 Heterogeneity in the Population

The empirical model captures heterogeneity in the population in three characteristics, including (1) rate of consumption of psychological inventory, (2) fraction of time available, and (3) activity set-up time.

4.2.1.1 Heterogeneous Consumption Rate

The rate of consumption of psychological inventory λ is heterogeneous in the population, and assumed to be distributed independently and identically with a lognormal distribution, whose underlying normal distribution has a mean μ_λ and variance σ_λ^2. Therefore, the distribution of the rate of consumption of psychological inventory λ_n for individual n is given as:

$$\lambda_n \sim LN(\mu_\lambda, \sigma_\lambda^2) \tag{4.2}$$

4.2.1.2 Heterogeneous Time Availability

The fraction of time available t, which is the amount of time available per unit time, is heterogeneous in the population, and assumed to be distributed with a lognormal distribution, whose underlying normal distribution has a mean μ_t and variance σ_t^2. Therefore, the distribution of the fraction of time available t_n for individual n is given as:

$$t_n \sim LN(\mu_t, \sigma_t^2) \tag{4.3}$$

4.2.1.3 Heterogeneous Set-up Time

The set-up time to conduct an activity, which is the minimum activity duration required to generate psychological inventory, is heterogeneous in the population, and assumed to be distributed with a lognormal distribution, whose underlying normal distribution has a mean μ_{T_0} and variance $\sigma_{T_0}^2$. Therefore, the distribution of set-up time T_{0n} for individual n is given as:

$$T_{0n} \sim LN(\mu_{T_0}, \sigma_{T_0}^2) \tag{4.4}$$

4.2.2 Empirical Model Specification

An empirical model of activity location, duration, and frequency choices is presented in this section. Apart from accounting for heterogeneity in the population characteristics, it also accounts for errors due to unobserved attributes, measurement errors, optimization errors on the part of the decision-maker, etc. Additionally, it models the effect of using aggregate location alternatives by including "size variables" in the model.

4.2.2.1 Location Choice

The observed location is subject to optimization errors on the part of the decision-maker and measurement errors in recording the chosen location. For individual n with optimal average level of inventory $\widetilde{I}_{avg,in}$ at location i, an error term, ϵ_{in}, with an Extreme Value Type I distribution (i.i.d., with location 0 and scale parameter μ) is added to the location choice optimization model. The location choice model transforms into a logit model under this assumption. Additionally, since the model aggregates elemental alternatives (e.g. shopping malls) into aggregate alternatives (Traffic Analysis Zones), a size measure (M_{in}), that reflects the size of location i for individual n, is included as a sum of weighted non-negative measures of size (e.g. retail employment, area of TAZ, see Ben-Akiva and Lerman, 1985). The second stage optimization model described in Section 3.3.1.2 may be rewritten as:

$$\underset{i}{Maximize} \quad \beta_I \widetilde{I}_{avg,in} + ln(M_{in}) + \epsilon_{in}, \epsilon_{in} \sim \text{Extreme Value Type I } (0, \mu) \tag{4.5}$$

$$M_{in} = \sum_{k'} \beta_{k'} x_{ik'n}; \ \beta_{k'} \geq 0, \ x_{ik'n} \geq 0, \ \forall i, k', n; \ \beta_{K'} = 1 \tag{4.6}$$

In Equation (4.6), k' indexes the set of size variables, $x_{ik'n}$ denotes the value of the k'^{th} size variable of alternative i for individual n, and $\beta_{k'}$ denotes the parameter of the k'^{th} size variable. If K' size variables are included in the specification, only $K' - 1$ parameters are identifiable (i.e. it is necessary to normalize the coefficient of one size variable, e.g. $\beta_{K'} = 1$).

Additionally, the first term $\widetilde{I}_{avg,in}$ is multiplied by a coefficient β_I to account for the scale of the utility function. It is necessary that $\beta_I > 0$ to ensure that the objective function maximizes (and does not minimize) the average level of inventory. Further, the value of $\widetilde{I}_{avg,in}$ may be substituted from Equation (3.21) in Equation (4.5) to rewrite the latter as:

$$\underset{i}{Maximize} \quad \beta_I(I_{sat,n} - \frac{1}{2}\widetilde{Q}_{in}) + ln(M_{in}) + \epsilon_{in}, \epsilon_{in} \sim \text{Extreme Value Type I } (0, \mu) \quad (4.7)$$

In Equation (4.7), $I_{sat,n}$ and $\widetilde{Q}_{in}$ denote the satiation limit of the psychological inventory of the need for individual n and the optimal activity production at location i for individual n, respectively. It may be noted that since the term $(\beta_I I_{sat,n})$ is constant across all location alternatives (since β_I is a model coefficient and $I_{sat,n}$ is a characteristic of the individual), it is unidentifiable (since only the differences in the values of the objective function across alternatives matter). To make the model identifiable, it may be rewritten as:

$$\underset{i}{Maximize} \quad -\beta_Q\widetilde{Q}_{in} + ln(M_{in}) + \epsilon_{in}, \epsilon_{in} \sim \text{Extreme Value Type I } (0, \mu) \quad (4.8)$$

In Equation (4.8), $\beta_Q (= \frac{1}{2}\beta_I)$ is a positive coefficient that accounts for the scale of the utility function. Given the set of model parameters including $\lambda_n, t_n, T_{0n}, \beta_Q$ and θ (where θ represents the coefficients in the activity production function), and normalizing the scale parameter ($\mu = 1$), the conditional probability P of individual n choosing location i_n may be written as:

$$P(i_n|\lambda_n, t_n, T_{0n}, \beta_Q, \mu, \theta) = \frac{exp(-\beta_Q\widetilde{Q}_{i_n n} + ln(M_{i_n n}))}{\sum_j exp(-\beta_Q\widetilde{Q}_{jn} + ln(M_{jn}))} \quad (4.9)$$

4.2.2.2 Duration Choice

For individual n, given the set of parameters λ_n, t_n, T_{0n} and θ, the optimal duration $\widetilde{T}_{ai_n,n}$ at his/her chosen location i_n is given by one that satisfies the time constraint, Equation

(3.19), as an equality. The observed duration, however, may contain measurement errors. To account for the measurement errors, a lognormally distributed multiplicative error term, whose underlying normal distribution has a mean 0 and variance σ_ν^2, is introduced into the model. Since the error term is always positive, the observed duration is also positive. The observed duration $T_{obs,n}$ for individual n who chose location i_n is written as:

$$T_{obs,n} = \widetilde{T}_{ai_n,n} exp(\nu_n) \ , \ \nu_n \sim N(0, \sigma_\nu^2) \tag{4.10}$$

Therefore, the conditional probability density f of the observed duration $T_{obs,n}$for individual n may be written as:

$$f(T_{obs,n}|i_n, \lambda_n, t_n, T_{0n}, \theta) = \frac{1}{T_{obs,n}\sigma_\nu}\phi(\frac{ln(T_{obs,n}) - ln(\widetilde{T}_{ai_n,n})}{\sigma_\nu}) \tag{4.11}$$

In Equation (4.11), $\phi(z)$ denotes the probability density function of a standard normal random variable z.

4.2.2.3 Frequency Choice

Under the steady-state assumption, the frequency with which individual n conducts the activity is given by the inverse of the cycle time. For individual n, given the set of parameters λ_n, t_n, T_{0n} and θ, the chosen location i_n, the optimal duration $\widetilde{T}_{ai_n,n}$ at location i_n, and hence the optimal activity production $\widetilde{Q}_{i_n n}$ at location i_n, the cycle time is given by $(\widetilde{Q}_{i_n n}/\lambda_n)$. If the individual conducts the activity once in $(\widetilde{Q}_{i_n n}/\lambda_n)$ units of time (e.g. days), then the probability of observing the individual conduct the activity on a random unit of time (i.e random day) is given by the frequency (or the inverse of the cycle time). Therefore, the conditional probability R of observing individual n conducting the activity during a random day is given by:

$$R(\delta_n = 1|i_n, \lambda_n, t_n, T_{0n}, \theta) = \frac{\lambda_n}{\widetilde{Q}_{i_n n}} \tag{4.12}$$

In Equation (4.12), δ_n refers to the frequency indicator defined in Equation (4.1). It must be noted that the model requires no knowledge about the last time the individual conducted the activity to predict the activity location, duration or frequency.

The error terms (i.e. ϵ_{in} and ν_n) introduced in this model and the heterogeneous parameters (i.e. λ_n, t_n and T_{0n}) are assumed to be uncorrelated.

4.3 Maximum Likelihood Estimator

This section incorporates the various elements of the empirical model described in Section 4.2 and develops a maximum likelihood estimator. The maximum likelihood estimator can be applied to single day travel diary data with no knowledge about the last time the activity was conducted.

The sample of respondents is divided into two groups of people, based on whether or not they performed the activity on the observed day. The likelihood functions for these two groups are developed separately, and then used to write the joint likelihood for a sample.

4.3.1 Likelihood Function for Individuals Who Performed the Activity on the Observed Day

For the group of individuals who performed the activity on the observed day, their activity location and duration are known. The joint likelihood for the activity location, duration and frequency for an individual belonging to this group is written as:

$$\begin{aligned} &l(\delta_n = 1, i_n, T_{obs,n}) \\ &= \int_{T_0}\int_t\int_\lambda \{R(\delta_n = 1|i_n, \lambda, t, T_0, \theta) f(T_{obs,n}|i_n, \lambda, t, T_0, \theta) \\ &\qquad P(i_n|\lambda, t, T_0, \beta_Q, \mu, \theta) h_1(\lambda) h_2(t) h_3(T_0)\} d\lambda dt\, dT_0 \end{aligned} \tag{4.13}$$

In Equation (4.13), R, f and P are as defined earlier in Section 4.2.2. The density functions of the consumption rate λ, fraction of time available t, and set-up time T_0 are given by h_1,h_2 and h_3, respectively.

4.3.2 Likelihood Function for Individuals Who Did Not Perform the Activity on the Observed Day

For the group of individuals who did not perform the activity on the observed day, no information is available on their chosen location or duration. Therefore, the likelihood of not observing the activity is written for an individual belonging to this group as:

$$\begin{aligned} l(\delta_n = 0) & \\ &= 1 - \int_{T_0}\int_t\int_\lambda \{\sum_i \{R(\delta_n = 1|i, \lambda, t, T_0, \theta) P(i|\lambda, t, T_0, \beta_Q, \mu, \theta)\} \\ &\qquad h_1(\lambda) h_2(t) h_3(T_0)\} d\lambda dt\, dT_0 \end{aligned} \quad (4.14)$$

In Equation (4.14), R, f and P are as defined in Section 4.2.2, and h_1, h_2 and h_3 are as defined in Section 4.3.1. Note that this likelihood is unconditioned on location, since this information is unknown. Moreover, since the probability of the individual conducting the activity on the observed day depends only on the chosen location and the optimal duration, this equation does not uncondition over the unobserved duration. In other words, while the chosen location and the optimal duration at that location affect the probability of the individual conducting the activity on the observed day, the unobserved (chosen) duration is considered to differ from the optimal value only due to measurement errors. Consequently, the density of the activity duration does not enter the likelihood function, and we do not uncondition over the unobserved (chosen) duration.

4.3.3 Likelihood Function for the Entire Sample

The likelihood function over the full sample of respondents can be expressed as:

$$\mathcal{L}^* = \prod_n (l(\delta_n = 1, i_n, T_{obs,n}))^{\delta_n} (l(\delta_n = 0))^{1-\delta_n} \tag{4.15}$$

This likelihood function may now be maximized to estimate the set of unknown parameters based on the observed data. It may be noted that in developing this empirical model, no assumption is made about the last time an activity was conducted before the observed day. The model relies on the steady-state assumption to develop the relationship between activity location, duration, and frequency choices and need-satisfaction.

4.4 Monte-Carlo Experiment

The estimator developed in Section 4.3 was tested on a synthetic sample generated using Monte-Carlo simulation. A sample of 2,000 individuals was created with a choice set consisting of 20 location alternatives (TAZs) for shopping activity. The retail employment in these zones was randomly generated between 1 to 100 employees per zone, and the area of the TAZs randomly from 0.1 to 2 mile^2. While the retail employment and area comprise the size variables that affect location choice, retail employment density, defined as the number of employees per unit area, was used as a measure of attractiveness in the activity production function. The retail employment density is a measure of the opportunities available to conduct shopping at a TAZ which does not vary by size (i.e. high retail employment density implies a large number of employees in retail per unit area in the TAZ). The travel times between these different zones were chosen to be uniformly distributed between 15 mins and 2 hours. Individuals in the sample were randomly assigned a home location from one of the 20 alternatives. The fraction of time available (t) was assumed to be deterministic, while the rate of consumption of psychological inventory (λ) and set-up time (T_0) were assumed to vary in the population. Given the distribution of the rate of consumption of psychological inventory (λ) and set-up time (T_0) in the population, values of λ and T_0 were assigned to every individual by simulating from their respective distributions. Their choice of shopping activity location, duration, and frequency was generated using the model. The resulting activity durations were in the range of 10 mins to 2 hours, with cycle times in the range of 3 to 7 days. Second order terms in the translog function were set to true values of zero for the synthetic data generation process. For each individual, the data contains an indicator of whether or not the activity was conducted on the observed day, and the location and duration if the activity was conducted.

Maximum likelihood estimation was performed using R statistical package (R Development Core Team, 2011). Given a set of parameters, the likelihood function was computed as follows. For each individual, the optimal duration at each location was first calculated by solving the time constraint as an equality. To do so, a non-linear equation solver routine was employed. Once the optimal duration was obtained for all locations, the likelihood was computed using the expressions developed in Section 4.3. To perform integration by simulation, 1000 Halton draws of the distributed parameters were used and the average of the likelihood over these draws was computed for each individual.

Ten parameters were estimated with a log-likelihood of -2677.77 at convergence. Two parameters, namely q_o and $\beta_{RetailEmp}$ had to be fixed (arbitrary normalization, to their true values in this case) to make the model identifiable. The estimation results shown in Table 4.1 indicate that the estimates are significantly different from 0 and are not significantly different from their true values. This shows that the model can estimate true parameters from observable data.

4.5 Case Study: Denver Metropolitan Area

This section presents a case study of an empirical application of the single need model to travel diary data from the Denver metropolitan area. A description of the data is provided, followed by estimation results.

Table 4.1: Estimation results from Monte Carlo experiment

Parameter	True Value	Estimate	Standard Error	t-stat (against 0)	t-stat (against true value)
q_0	0	0	Fixed	-	-
q_1	5.0000E-01	4.9149E-01	1.3368E-01	3.68	-0.06
q_2	5.0000E-01	4.9973E-01	8.0961E-02	6.17	0.01
t	1.0000E-01	1.0164E-02	3.0170E-04	33.69	0.54
μ_λ	-5.0000E-00	-5.0013E+00	4.7247E-01	-10.59	0.03
σ_λ	1.0000E-01	8.8216E-02	1.4576E-02	6.05	-0.81
μ_{T_0}	1.3863E+00	1.3534E+00	5.0066E-01	2.70	-0.06
σ_{T_0}	1.0000E-01	1.0591E-01	2.1684E-01	0.49	0.03
β_Q	1.0000E+00	1.0043E+00	4.7215E-01	2.13	0.01
$\beta_{RetailEmp}$	1.0000E+00	1	Fixed	-	-
β_{Area}	7.0000E-01	6.3804E-01	1.5092E-01	4.23	-0.41
σ_ν	2.0000E-01	2.1539E-01	1.7039E-02	12.64	0.90

4.5.1 Data

The travel diary data used in this case study was collected by the Denver Regional Council of Governments (DRCOG) in the year 2009 to develop travel demand model systems for planning purposes. Complete activity patterns were recorded for 15,323 individuals. Detailed information is available about the purpose, location, mode, time-of-travel, travel time and activity duration for each trip and the activity conducted at the destination of the trip.

This case study develops a model of activity location, duration and frequency choices for shopping conducted as the primary activity of a day. To extract information about shopping as primary activity of the day, the trips reported in the survey were processed to form tours. A tour was identified as a set of trip-chains starting and ending at the same location. Based on whether this location was home or work place, the tour was classified as home-based or work-based. The primary activity of the tour was then determined based on priorities assigned to different activity purposes and activity durations. Once the tours were formed, similary priority rules were employed to identify the primary activity of the day. The activity with the highest priority from the list of all primary activities on tours conducted on the day was marked as the primary activity of the day.

The individuals in the sample can be divided into two groups, including (1) individuals who conducted shopping as the primary activity of the day on the observed day and reported their shopping activity location and duration, and (2) individuals who did not conduct shopping as the primary activity of the day and therefore did not report their shopping activity location and duration. Out of all the individuals belonging to the second group, those who conducted work as the primary activity of the day were excluded to account for differences in their lifestyle that may prevent them from conducting shopping as the primary activity of a day.

It was found that all shopping activities reported by children below the age of 16 years were conducted along with an adult in the household. Therefore, observations of shopping conducted by children were removed. In case of joint shopping activity participation by several adult members (16 years or over) of a household, only one record per joint activity was retained in the sample. The efficiency gained by jointly conducting the activity was modeled by including the number of individuals who conducted the activity together as an input in the activity production function. For households in which no individuals conducted shopping as the primary activity of the day but at least one adult did not conduct work as the primary activity of the day, one observation was included in the dataset. In this case, the number of individuals who jointly conducted the activity was computed as described further below.

A total of 5260 observations were obtained, of which 811 correspond to those where shopping was conducted as the primary activity of the day. For the location choice, a total of 2804 Traffic Analysis Zones were available in the universal choice set. For each individual, a subset of location alternatives (including the individual's chosen location if the activity was observed) were sampled without replacement from the universal choice set. For each location alternative, retail employment density in the TAZ was used a measure of attractiveness, while retail employment and area of TAZ were used as size variables. Additionally, travel time from the individual's home TAZ to each location alternative was extracted from the DRCOG skim database. This database provided travel time information by mode and time-of-travel. For individuals who conducted the activity, the chosen mode and time-of-travel were known, and were used to determine the travel time to different locations. For individuals who did not conduct the activity, (1) mode was determined as auto if the individual was over 16 years and the household owned at least one vehicle and as transit otherwise, and (2) time-of-travel was determined to be off-peak since the activity in question is shopping.

4.5.2 Empirical Estimation

The needs-based model was estimated empirically for shopping as primary activity of the day. To reduce the computational complexity, the model included only first order terms in the activity production function. The resulting activity production function may be represented as:

$$Q = exp(q_0 + q_1 ln(T_a - T_0) + q_2 ln(A) + q_3 ln(N_p)) \tag{4.16}$$

In Equation (4.16), the number of individuals in the party that conducted the shopping activity (N_p) is included as an additional input to the activity production function. For observations where the activity was conducted, N_p was observed. For observations where the activity was not conducted, N_p was unobserved and was computed in two different ways, including (1) as the number of adults in the household, and (2) one. To ensure monotonicity and concavity of the activity production function, the coefficients q_1, q_2 and q_3 were constrained between 0 and 1 by using a logistic transformation as shown below, where the parameters r_1, r_2 and r_3 were unconstrained:

$$q_k = \frac{1}{1 + e^{r_k}};\ k = 1, 2, 3 \tag{4.17}$$

The coefficient q_3 was statistically insignificant, irrespective of whether N_p was computed as the number of adults in the household or one. Therefore, N_p was dropped from the activity production function. Similarly, the coefficient q_1 attained its upper bound and therefore was fixed to a value of 1 for the purpose of estimation.

The model included heterogeneity in two parameters, including (1) rate of consumption of psychological inventory, and (2) fraction of time available. Heterogeneity in set-up time parameter was not included in the model. Two size variables were used, including (1) retail employment in the TAZ, whose coefficient was estimated, and (2) area of the TAZ, whose coefficient was normalized to 1.

Estimation of the model on a 100-core cluster computer with parallelized computation of the likelihood function took 7 days with 1000 Halton draws for randomly distributed parameters. The model was estimated from multiple starting values to yield different local optima. In Table 4.2, the best model with estimates that yielded the highest value of log-likelihood across different starting values is presented. The value of the log-likelihood at these estimates was found to be -7089.79.

Table 4.2: Denver case study: Estimation results for a model of activity location, duration and frequency choices for shopping as primary activity of a day

Parameter	Estimate	Standard Error	t-stat (against 0)
q_0	0	Fixed	-
q_1	1	Fixed	-
q_2	3.7543E-07	6.4992E-05	0.01
μ_t	3.2088E+00	3.6329E-02	88.33
σ_t	4.2362E-02	2.1017E-02	2.02
μ_λ	2.7942E+00	5.2816E-02	52.90
σ_λ	8.6140E-02	1.3600E-02	6.33
μ_{T_0}	3.1096E+00	3.2032E-01	9.71
β_Q	7.2452E-02	7.0500E-03	10.28
$\beta_{Retail Emp}$	2.2685E-03	4.9698E-04	4.56
β_{Area}	1	Fixed	-
σ_ν	4.2318E-01	1.4422E-02	29.34

Estimation results indicate that q_2 is insignificant, implying that only the effective activity duration has an impact on the activity production function. The fraction of time available is found to have a mean value of 24.77 min/day with a standard deviation of 1.04 min/day. It may be noted that the average cycle time observed in the sample, computed as the inverse of the fraction of observations which reported that a shopping activity was conducted, is found to be approximately 7 days. Therefore, the time availability per average cycle is computed to have a mean value of 171.43 min and standard deviation of 7.26 min. This result is consistent with the sample statistics of the total time spent conducting shopping, which indicate a mean activity duration of 120 min and mean travel time of 50 min approximately. Additionally, the set-up time parameter is estimated to be 22.41 min, which indicates a mean effective activity duration of approximately 98 min.

The estimation results presented in Table 4.2 underscore the potential of the needs-based approach to developing activity-based models. Socio-economic characteristics of households and travelers must be included in the model to enhance its specification. Further, the model must be extended by developing models of (1) shopping as secondary activity of the day, and (2) other activity purposes (e.g. recreation).

Online shopping can also be modeled within the needs-based framework by including online shopping as an alternative in the location choice set. The attractiveness of this alternative can be modeled using a dummy variable (replacing attractiveness A_i in the activity production function). In the Denver dataset, individuals reported the duration for online shopping by specifying the time at which the previous home-bound trip ended and the time at which the next trip away from home began. However, the exact duration spent conducting online shopping is unknown since the individual may have conducted other activites at home during this duration. Therefore, it is necessary to model the activity duration as a latent variable in the model. However, since only 24 online shopping observations were recorded in the data, online shopping was not modeled in this case study.

4.6 Conclusion

This chapter developed an empirical model of activity location, duration, and frequency based on the theoretical model for a single need developed in Chapter 3. The empirical model accounts for (1) heterogeneity in characteristics including fraction of time available, rate of consumption of psychological inventory, activity set-up time, etc., (2) measurement errors and unobserved attributes in location choice, (3) measurement errors in duration choice, and (4) the effect of size variables in the location choice model to account for the use of aggregate location alternatives (i.e. TAZs instead of actual activity locations like retail spaces). A maximum likelihood estimator was developed to estimate the model from single day travel diary data with no knowledge about the last time the activity was conducted. A Monte Carlo experiment was conducted to verify that the model can recover true parameters from observable data. Finally, the model was estimated using standard travel diary data from the Denver metropolitan area for shopping conducted as the primary activity of the day. Estimation results indicate that the needs-based approach has great potential to enrich the specification of activity generation models in conventional activity-based model systems. However, in light of the long computational time reported for the estimation of these models, their practical applicability must be studied using larger datasets and more efficient computational methods.

5 Conceptual Framework for Extensions of Needs-based Models

This chapter develops a conceptual framework to extend[1] the single need - single activity model developed in Chapters 3 and 4. First, extensions of the single need model are discussed, including (1) inclusion of mode and time-of-travel choices, and (2) multiple activities satisfying a single need. A discussion on the extension to a model of multiple needs follows. Further, the framework can be extended to model social interactions to account for the fact that activities conducted by an individual may affect not only his/her need-satisfaction but also that of a household or social circle. Intra-household activity allocation and joint activity participation are presented as potential directions for extensions. Finally, since the notion of time varying psychological inventory naturally provides a framework to study temporal variations in need-satisfaction and activity choices, development of dynamic needs-based models that can be estimated from multi-day travel surveys is discussed as an extension.

5.1 Single Need Steady-state Model

This section discusses enhancements to the single need model developed in Chapter 3. Two extensions are discussed, including (1) inclusion of mode and time-of-travel decisions, and

[1]The ideas presented in this chapter benefited from discussions with Carlos Carrion, Roger Chen and Giulia Cernicchiaro.

(2) multiple activities conducted to satisfy a single need.

5.1.1 Inclusion of Mode and Time-of-travel Decisions

The model developed in Chapter 3 describes individuals' activity location, duration and frequency choices only. The framework can easily be extended to include mode and time-of-travel decisions for the trips leading to the activities, since these choices enter the model through the travel time and location attractiveness variables. Clearly, travel time varies by time-of-travel (e.g. greater travel time in peak period than in off-peak period) and mode (e.g. greater travel time by transit than by auto). While the attractiveness of a location does not vary by mode or time-of-travel, these factors affect an individual's location choice set. For example, a recreational activity like watching a movie at a cinema can only be performed when the movie is screened at the cinema. During these movie screening hours, the cinema is available in the individual's choice set. During other times, this location is unavailable in the individual's choice set.

The model developed in Chapter 3 may be extended to jointly model activity location, mode, time-of-travel, duration and frequency. While mode choice is a discrete optimization problem, time-of-travel can also be modeled as a discrete optimization problem with a choice set created by dividing a day into time periods (e.g. AM peak, PM peak, off-peak, etc.). The optimization problem is solved in two stages in a manner similar to the solution procedure proposed in Chapter 3. In the first stage, the optimal duration and frequency are computed for each location, mode and time-of-travel combination. In the second stage, the combination of location, mode and time-of-travel that maximizes the objective function (average level of psychological inventory over time) is determined as the optimal solution to the problem. To estimate this needs-based model empirically, a nested logit model structure as shown in Figure 5.1 may be used to model location, mode, and time-of-travel jointly in a discrete choice framework along with frequency and duration choice models as in the model in Chapter 3. Different nesting structures must be tested empirically to choose the best specification. The systematic utility of each alternative, defined as the combination of the location, mode and time-of-travel, is given by the optimal average level of inventory computed by solving the first stage optimization model.

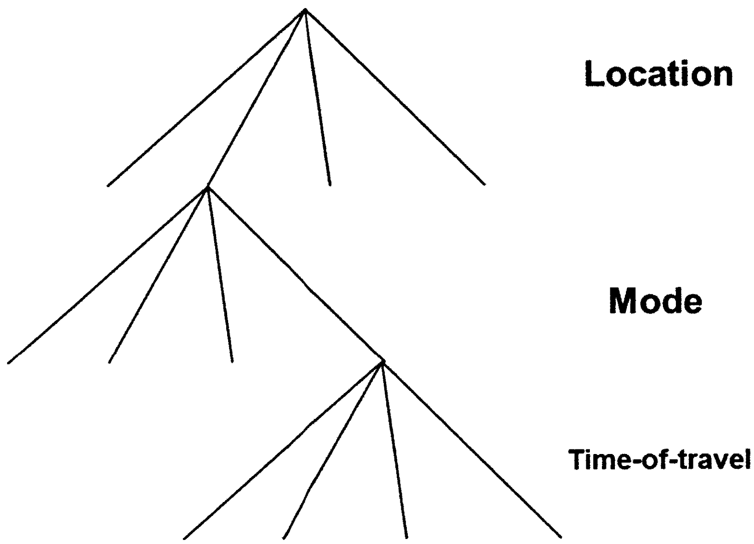

Figure 5.1: Nested logit structure for location, mode and time-of-travel choices

This extension extends the framework to model mode and time-of-travel choices, keeping the formulation in Chapter 3 intact. However, it must be noted that the choice set for the discrete choice model might be very large and would require sampling of alternatives for estimation.

5.1.2 Single Need and Multiple Activities

The assumption of a single activity satisfying one need that was made in Chapter 3 is restrictive since several activities can satisfy a single need. For example, the need for recreation may be satisfied by watching a movie at home, going out to the theater, playing a sport, etc. This may be explained as variety-seeking behavior of the individual. This section extends the model formulated in Chapter 3 to the case of multiple activities satisfying a single need.

Figure 5.2 illustrates the evolution of psychological inventory for the case of two activities satisfying a single need. In this figure, two activities with activity production of Q_1 and Q_2 are conducted at times (T_1, T_3) and (T_2, T_4), respectively. The psychological inventory is related to the need and not the activities, and therefore is unidimensional (as against the multiple needs case, where the inventory is multidimensional). This general formulation allows for several activities satisfying the same need to be conducted on different days. The two activities may be conducted on different days, and the lag between the two activities is an individual's choice which can be modeled as a choice of different minimum levels of inventory at which each activity is triggered (i.e. $I_{min,1}, I_{min,2}$). Additionally, the individual chooses the locations, durations, and frequencies of both activities.

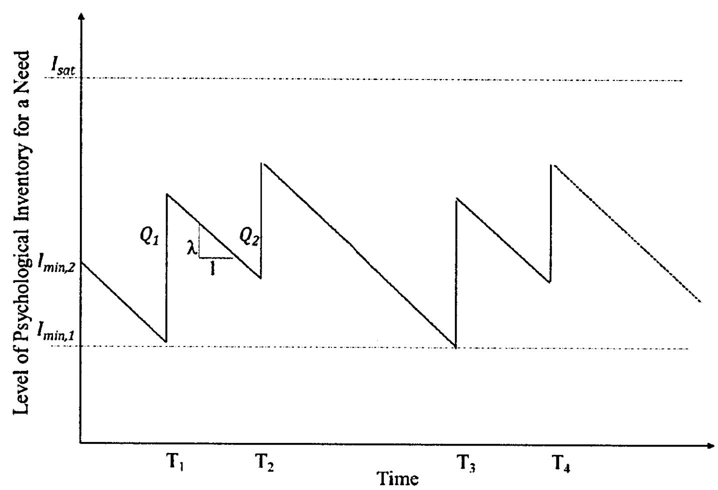

Figure 5.2: Psychological inventory of a single need satisfied by two activities

It is important to note that the individual conducts both activities to satisfy the same need, since doing so provides a greater value of the average level of psychological inventory than conducting only one of the activities. Therefore, the joint activity production function of the two activities must account for the frequency at which the activities are conducted. In other words, the joint activity production of the two activities must be modeled as a function of the activity productions of the two activities which includes interaction terms between the two activities. This is necessary to ensure that the individual's variety-seeking behavior is modeled.

A special case of this formulation is shown in Figure 5.3, where both activities satisfying the need are conducted on the same day (such that the depletion of inventory between the performance of both activities is negligible). In this case, the overall cycle time is $\frac{(Q_1+Q_2)}{\lambda}$. This model can be solved using a procedure similar to the one developed in Chapter 3.

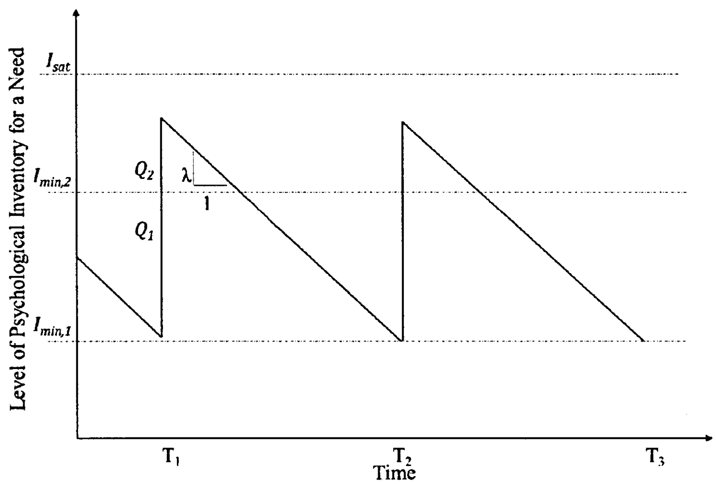

Figure 5.3: Psychological inventory of a single need satisfied by two activities performed on the same day

5.2 Multiple Needs Steady-state Model

In this section, the extension of the single need model to the general case of multiple needs is discussed. In reality, individuals conduct several activities, each of which may satisfy several needs. For example, to satisfy the need for nutrition, an individual may eat food at home with a partner, or go out to a restaurant with friends. While the former activity additionally satisfies the need for security and intimacy, the latter satisfies the need for relatedness and social interaction. Therefore, the choice of activities is affected by the desire to satisfy multiple needs by performing different activities given limited availability of time and money.

In modeling interactions between multiple needs and the activities that satisfy them, it is important to develop an understanding of the relationship between each activity and the needs it satisfies. It is important to note here that while the activities are observed, the needs are latent and unobserved. To characterize the impact of different activities on need-satisfaction, a satisfaction matrix as shown in Table 5.1 may be constructed. Each row in this table corresponds to a need (e.g. nutrition/nourishment, security and intimacy) while each column corresponds to an activity conducted to satisfy this need (e.g. eat dinner at a restaurant, watch a movie at a cinema). The individual conducts A activities to satisfy K needs. Each element in the matrix represents the contribution of the corresponding activity's production to the need. In other words, in Table 5.1, if conducting activity 2 generates an Q_2 units of inventory, it contributes $Q_2^1 = w_{12}Q_2$ units of inventory to satisfy need 1 and $Q_2^2 = w_{22}Q_2$ units of inventory to satisfy need 2. In this example, activity 2 does not satisfy needs 3,...,K.

Table 5.1: Satisfaction matrix of needs and activities

	Activity 1	Activity 2	...	Activity A
Need 1	w_{11}	w_{12}	...	w_{1A}
Need 2	0	w_{22}	...	w_{2A}
$\vdots$	0	0	0	$\vdots$
Need K	0	0	...	w_{KA}

A satisfaction matrix may be constructed either using (1) a confirmatory approach, or (2) an exploratory approach. The confirmatory approach is one in which the elements in the satisfaction matrix are prespecified based on apriori hypothesis. For example, if it is known that going to the movie does not satisfy an individual's recreational need, the corresponding element in the satisfaction matrix can be set to 0. In an exploratory approach, empirical analysis of activity diary data is performed to learn about the distribution of activity production to different needs. It may be desirable to collect data about individuals' need-satisfaction as a part of travel survey, to enable better exploratory analysis.

Figure 5.4 illustrates the evolution of an individual's psychological inventory of two needs over time.

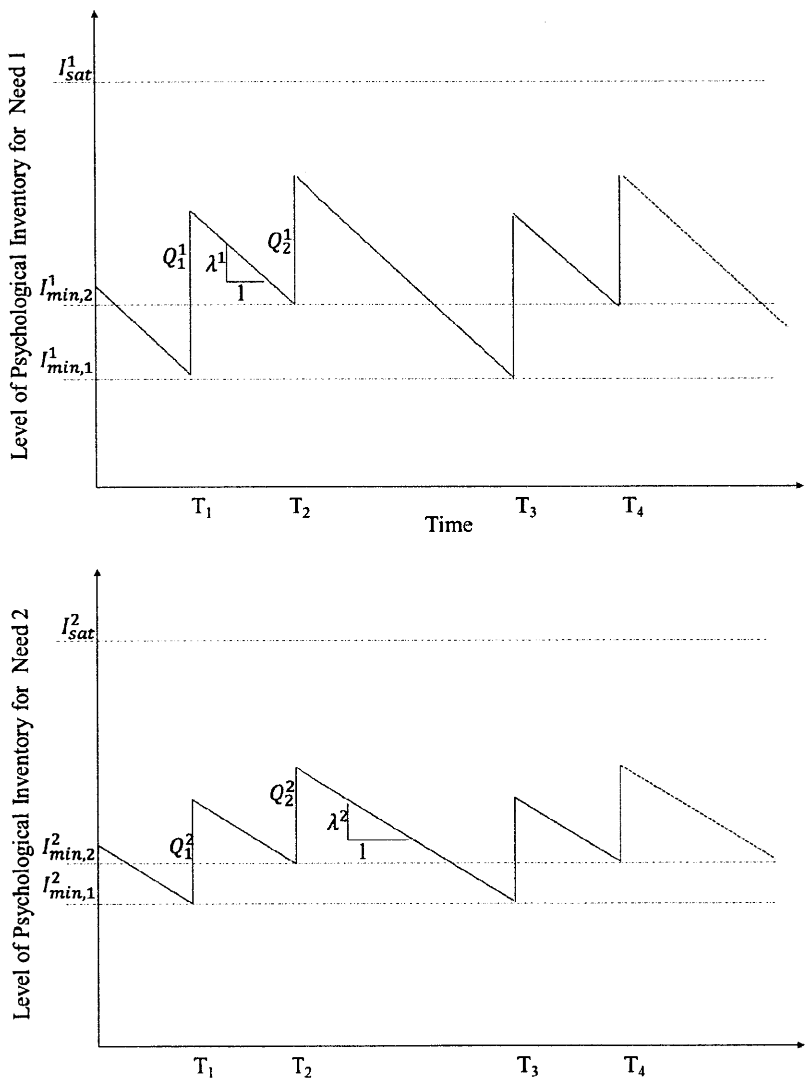

Figure 5.4: Psychological inventory of two needs that are both satisfied by two activities

The individual conducts two activities that satisfy both needs, by choosing the locations, durations, frequencies, and minimum levels of psychological inventory for both activities with respect to both needs. For the first need (1), the two activities produce Q_1^1 and Q_2^1 units of inventory, while for the second need (2), the two activities produce Q_1^2 and Q_2^2 units of inventory.

The objective that the individual maximizes is a function of both inventories with respect to both needs. In other words, this is an optimization problem with a multidimensional objective function. A common approach to formulate a multidimensional objective function is as a weighted sum of the various dimensions. In other words, the objective may be modeled as the weighted sum of the average levels of psychological inventory with respect to the different (in this example, two) needs. The weights may be estimated empirically from activity diary data.

Alternatively, a max-min formulation may be used which tries to maximize the minimum of average level of psychological inventory across needs. This approach would not involve the use of potentially arbitarary weights, and would also ensure that the extreme value of the inventory (i.e. the minimum) is explicitly maximized to account for the effect of variation of inventory over time in the choices.

A detailed discussion of multi-objective optimization is beyond the scope of this thesis. The interested reader is referred to Deb (2005) for a review of different approaches to formulate and solve multi-objective optimization problems.

The model also additionally imposes time and cost budget constraints to reflect limited availability of time and cost. However, it is important to note that since the optimization problem models decisions about multiple activities satisfying multiple needs jointly, the model must include a single time constraint and a single cost constraint that models the time and money spent on all the activities.

5.3 Social Interactions and Joint Activity Decisions

The needs-based approach provides a framework to model interactions between individuals that affect their activity choices. Two main extensions are identified here, which affect activity choices of individuals and households.

1. Certain household activities like grocery shopping are performed by one or many of the individuals to satisfy the needs of the household. This may be captured in the needs-based framework by modeling psychological inventory of households, apart from that of individuals. In doing so, an individual's inventory may be modeled as affected by both his/her own inventory and that of his/her household. Under this framework, the allocation of activities to individuals may be modeled as a choice driven by the maximization of need-satisfaction of all the individuals in the household, subject to availability of time and income.

2. Joint activity participation may also be modeled in this framework. First, some activities require mandatory joint participation of household members, or of members of a social circle. For example, escorting a child to/from day care is an activity that can only be carried out by the child with an adult in the household. Joint participation of this kind may be modeled as constraints in the problem. On the other hand, some other activities may be conducted jointly with family or friends to (1) satisfy the need for relatedness and social interaction, and (2) to increase the efficiency with which the activity is conducted since more human resources are now available to conduct the same activity. In doing so, the choices of activity location, duration, frequency, etc. are determined jointly for the social circle that conducts the activity together. This imposes greater rigidity in the performance and scheduling of these activities since it involves the coordination of schedules by multiple individuals. Additionally, the model may capture the effect of social interaction on location choice through the attractiveness of locations. For example, an individual is likely to perceive a shopping mall that his/her friends frequent to be more attractive than other shopping malls, since the for-

mer also offers the opportunity to satisfy both the need for shopping (sustenance) and for relatedness and social interaction. In other words, one may formulate the problem with a more flexible interpretation of the attractiveness variable (as opposed to fixed measures such as retail employment density) to model the effect of social interactions. Finally, the effect of increase in efficiency due to joint activity participation may be captured by including the number of individuals in the party as an additional input in the activity production function.

Models accounting for joint needs and joint activity participation may draw ideas from the area of cooperative game theory. In this approach, individuals who jointly perform tasks try to maximize their individual as well as group needs, by accounting for the trade-offs in making decisions that either satisfy only individual needs or only group needs. The interested reader is referred to Chiappori (1988) and Chiappori and Ekeland (2009) for a review of these approaches. de Palma et al. (2011) studied the balance of power in household decisions and concluded that in joint household decisions, men have more decision-making power initially, while women gained greater decision-making power as the decision was being implemented. They also concluded that men spent greater amount of resources on their individual needs, while women spent greater amount of resources on satisfying household needs.

It is important, therefore, (1) to account for cooperative game theoretic behavior in joint decision making by households and social cricles, and (2) to understand the dynamics of power sharing between different individuals in the group which affects how joint activity decisions are made.

5.4 Dynamic Needs-based Model

The discussion in this thesis has been focussed on a steady-state formulation that assumes that individuals conduct activities at the same locations, for the same durations, and at a constant frequency over time. However, in reality there is a lot of variability in individuals' activity choices. The formulation that was developed in Chapter 3 may be viewed as representative of long term behavior of individuals, while the variability that is not captured by the model may be viewed as short term variation in choices. An extension of the needs-based model to a dynamic context would relax the steady-state assumptions made in Chapter 3 and allow us to model short term variation in activity choices. While the steady-state model may be viewed as generating activity plans for individuals, the dynamic model is well-suited to predict individuals' real-time activity choices in response to transportation network conditions. This section discusses three important concepts that are of interest to dynamic models, including (1) time discounting and preferences, (2) nonconstant rate of consumption of psychological inventory, and (3) plan and action model.

5.4.1 Time Discounting and Preferences

In the dynamic context, the choices of activity dimensions (e.g. location, duration, frequency, etc.) are no longer considered to be constant over time. Figure 5.5 illustrates the evolution of an individual's psychological inventory of a need in the dynamic case, where the individual conducts activities that satisfy the need at times T_1, T_2, etc. with different dimensions on each occasion (i.e. different location, duration, frequency, etc. to produce different quantities of inventory on each occasion).

The optimization problem may be formulated as one that maximizes the total level of inventory over time, e.g. over a planning horizon. At the begining of this time horizon, the individual makes activity choices that maximize his/her need-satisfaction over the planning horizon. However, it is important to account for time discounting in preferences. Literature in behavioral economics suggests that individuals weigh the effect of events in the near future much higher than the effect of events in the distant future. In other words, future events are discounted and thus play a smaller role in an individual's decision as against immediate events that have a greater impact on their decisions. The notion of "hyperbolic" discount-

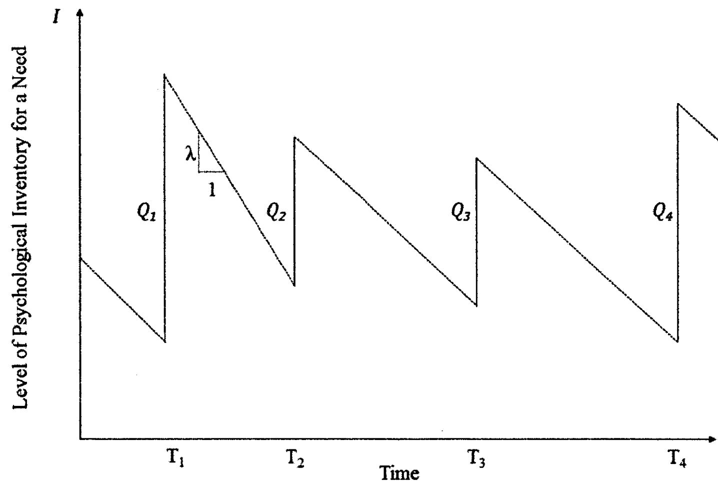

Figure 5.5: Dynamic model of evolution of psychological inventory of a need

ing, wherein the discount rate is a hyperbolic function of time, has also been studied in the literature (see, for example, Prelec, 2004). In other words, individuals are more perceptive to changes in events in the near future, while are affected less by changes in events that occur in the far future. For a detailed review of the literature on time discounting and time preferences, the interested reader is referred to Frederick et al. (2002).

5.4.2 Nonconstant Rate of Consumption of Psychological Inventory

In the steady-state single need model developed in Chapter 3, the rate of consumption of psychological inventory (λ) was assumed to be constant over time. Since the temporal variation in the rate affects the individual's frequency choice, this assumption is restrictive. For example, if an individual's inventory was recently replenished (and its value is high), it is likely to deplete at a slower rate than if it was replenished long ago (and its value is low). It can be relaxed by allowing the rate of consumption of inventory to be a function of the level of inventory at any point in time (i.e. $\lambda = \lambda(I)$, see Figure 5.6). It is important to study the shape of the $\lambda(I)$ curve and determine empirically whether the inventory is (1) concave, (2) convex, or (3) both concave and convex.

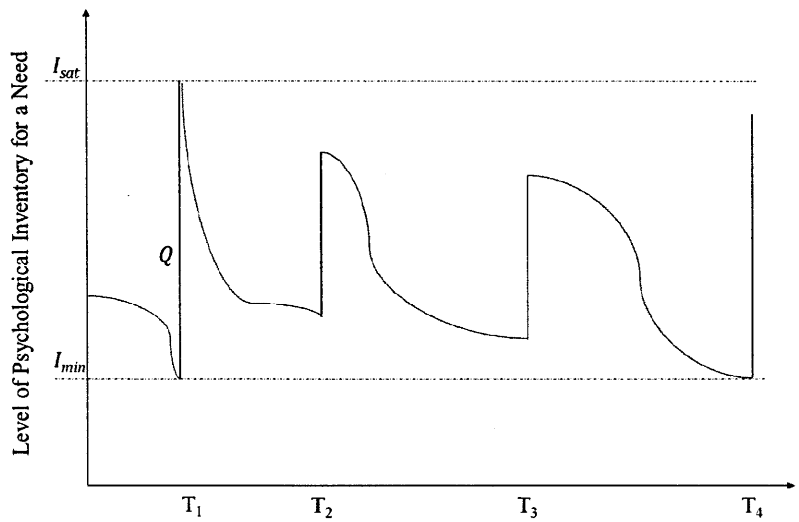

Figure 5.6: Psychological inventory over time with nonconstant rate of consumption of inventory

5.4.3 Plan and Action Framework

Further, the dynamic case may be modeled using a plan-action framework which uses a Hidden Markov Model (see Ben-Akiva, 2010). The time period (e.g. week) for which the activity choices are modeled is divided into smaller periods (e.g. days). In this framework, the steady-state model similar to the one developed in Chapter 3 is used to develop latent "plans" for the individual for the entire week. A dynamic model is then used to execute an "action", based on the plan for the current time period, which is affected by the previous plan and the action executed in the previous time period. Consequently, this approach would allow individuals to choose between different latent plans to execute the one that maximizes the psychological inventory of needs.

5.4.4 Trip Chaining Behavior

Individuals form trip chains to conduct multiple activities on a single tour since it provides greater travel efficiency. Several models of trip chaining behavior have been developed (see, Adler and Ben-Akiva, 1979 for a model of trip chaining behavior for non-work travel). In the needs-based model, trip chaining can be modeled as part of a dynamic framework in which individuals execute their planned activities by forming trip chains to minimize their time spent on travel and have more time available to conduct activities.

A key requirement for the empirical estimation of dynamic models is the availability of multi-day activity diary data. With increasing deployment of smart phone based, GPS enabled travel surveys, the estimation of dynamic models is likely to be feasible.

5.5 Conclusion

This chapter presented directions for future research using the needs-based model. Extensions to the single need model include (1) modeling mode and time-of-travel choices, and (2) multiple activities satisfying a single need. The extension to multiple needs provides an activity generation model system that can be fully integrated with conventional activity-based model systems. Extensions to model intra-household activity allocation and joint activity participation by members from a household and a social circle were discussed. Finally, a conceptual framework to develop a dynamic needs-based model was presented, based on which individuals' activity rescheduling decisions in response to real time transportation network conditions may be modeled.

6 Conclusion

This chapter summarizes the motivation for this thesis, research reported in the thesis and the key contributions. Directions for future research are also suggested.

6.1 Motivation, Summary, and Contributions

The activity generation models in conventional activity-based travel demand model systems are specified based on empirical considerations, and are weakly founded in a behavioral theory. This thesis aims to contribute to the body of research that enhances the specification of activity generation models.

This thesis develops a conceptual framework to study the relationship between individuals' activity participation and need-satisfaction. The theory of needs hypothesizes that individuals conduct activities to satisfy their needs. The thesis develops a utility-maximizing optimization model, which describes the choice of activity dimensions including frequency, sequence, location, mode, time-of-travel, etc. as one that maximizes an individual's need-satisfaction. Every need is associated with a level of psychological inventory, which reflects the level of need-satisfaction at any point in time. As the need builds up, the inventory gets depleted. Each time an individual conducts an activity that satisfies the need, the inventory is replenished by a quantity called the activity production, that is a function of the activity inputs including duration, expenditure, and location attractiveness. Individuals choose locations, durations, and frequencies of activities so as to maximize their psychological inventory of needs subject to time and budget constraints. This thesis develops an analytical model and proposes a solution procedure for a model of single need and the activity that satisfies the need under steady state conditions. The solution properties are studied and verified for a translog functional form of activity production. The solution is found to exhibit desirable properties governing the relationships between activity participation and satisfaction of needs. Based on the theoretical model, an empirical model is developed which can be estimated using standard one-day travel diary data with no knowledge of the last time the activity was performed. The empirical model explicitly accounts for heterogeneity in individuals' characteristics, including availability of time, rate of consumption of psychological inventory, etc. A Monte Carlo experiment is conducted to verify that the model can recover true parameters from observable data.

A framework for extensions to the single need steady-state model is presented. Two extensions of the single need model are discussed, including (1) incorporation of mode and time-of-travel choices, and (2) a model of multiple activities satisfying a single need. Extension of the single need model to multiple needs is discussed. A discussion on joint household needs follows, which enables modeling of intra-household activity allocation and joint activity participation by households and social circles. Finally, extensions to dynamic needs-based models are discussed, which will allow the development of models of activity rescheduling choices in response to real-time transportation network information.

A key contribution of this thesis is the development of an analytical framework to develop behaviorally enriched activity generation models. The needs-based models can be integrated with conventional activity-based model systems to replace the existing models that are weakly founded in a behavioral theory. The single need model can be developed for all the activities an individual conducts to independently model the choices for each activity an individual conducts. This model enhances the state-of-the-art of activity generation models by explaining the choice of activities based on a behavioral theory, as against existing models of activity generation. The framework provided by the thesis may be used to develop a model of multiple needs and activities to develop enhanced activity generation models which explicitly model the trade-offs between different needs that an individual wants to satisfy. The applicability of the modeling approach is greatly enhanced by its ability to incorporate joint needs of households and social circles. Dynamic needs-based models developed based on the conceptual framework discussed in this thesis may be integrated with the steady-state models developed in this thesis to provide a comprehensive behavioral model system for activity scheduling and rescheduling decisions. These models can then be deployed in transportation simulators to generate disaggregate travel demand which is sensitive to individuals' response to real-time information systems.

6.2 Directions for Future Research

This thesis has presented a new approach to model activity choices of individuals for travel demand analysis. To a large extent, the models developed are preliminary and would benefit from greater inquiry. The directions for future research, based on the extensions discussed in Chapter 5, are summarized here.

1. Empirical estimation of single need - single activity model: The estimation results presented in this thesis are exploratory and may be viewed as a proof of concept. The model must be estimated with additional activity diary data to verify that the empirical models satisfy the desired properties. The effect of socio-economic variables on various latent parameters including activity production, rate of consumption of psychological inventory, etc. must be explored. Further, different functional forms for the activity production function must be explored.

2. Extensions of single need model: Two main directions to extend models of single need were discussed in Chapter 5. These include models with (1) mode and time-of-travel decisions in the model framework, and (2) multiple activities satisfying a single need.

3. Extensions to multiple needs model: Models of multiple needs must be developed that explicitly account for the trade-offs individuals face while making decisions about multiple activities. Different model formulations are possible since this is a multi-dimensional optimization problem.

4. Extension to joint needs model: Models of joint need-satisfaction and activity participation may be developed based on the framework developed here. Two main directions include modeling (1) intra-household activity allocation, and (2) joint activity participation by members of a household and a social circle.

5. Dynamic needs-based models: The time varying nature of psychological inventory lends itself to the extension of these models to a dynamic framework. Models of activity rescheduling, which consider real-time transportation network conditions and deduce the opportunities or constraints the real-time scenarios create, may be developed.

6. Incorporation of well-being indicators: The approach proposed by Abou-Zeid (2009) may be applied to the needs-based model framework to measure and incorporate into needs-based models, measures of needs, activity and travel well-being, satisfaction and happiness. The benefits from including these indicators, including gain in efficiency of estimates, may be verified in the context of needs-based models.

7. Integration with conventional activity-based model systems: A key step in operationalizing needs-based models is integrating them with conventional activity-based models based on the day activity schedule approach. Research effort may be directed to identify how the needs-based models may be integrated with existing models.

8. Integrated Transportation Energy and Activity Modeling (iTEAM): The notion that individuals conduct activities to satisfy their needs is appealing and can be extended to model their consumption of other resources including energy. Integrated modeling of transportation and energy has received great interest in recent times, and may be enhanced by adopting a needs-based approach (see, for example, Gauche, 2010).

6.3 Conclusion

Drawing on the theory of needs, this thesis has contributed to enhancing the behavioral richness of activity-based models. It has developed conceptual and analytical frameworks to describe the relationship between individuals' need-satisfaction and activity choices. The methods developed in this thesis are useful not just to model transportation demand, but also demand for other resources (e.g. energy).

The results presented in this thesis are exploratory in nature. The models developed here must be empirically estimated with larger datasets to test their practical applicability and feasibility.

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